EXHIBIT 23

ZCCX249 - Phillip Areeda, Herbert Hovenkamp, Roger D. Blair, & Christine Piette Durrance, Antitrust Law: An Analysis of Antitrust Principles and Their Application (4th ed. 2014), Volume IIA

Part 2

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mathematical) relationship between the independent variables and the dependent variable. In other words, the value of S is dependent on the values of X_1, X_2, and X_3 and, conversely, X_1, X_2, and X_3 determine or explain the value of S.

The second step in regression analysis is to create an econometric model based on the theoretical model. Start by selecting a specific functional form that appropriately relates the independent variables with the dependent variable. For most practical purposes, a linear relationship is assumed, at least initially. Selection of a linear relationship means that the independent variables are related to the dependent variable in a linear way. For example, if we relate the surrounding population to restaurant sales in a linear model, we assume that for every unit increase in the surrounding population, there is an associated increase in sales revenue. The change in sales revenue is the same for every one-unit change in population. In other words, the slope is constant. The economic model will be written as follows:

$$S = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3. \qquad [2]$$

This specification indicates that the total sales revenue equals some constant amount (β_0) plus a variable amount that is determined by the value of each of the explanatory variables. The letters β_0, β_1, β_2, and β_3 in this model are known as the model's *parameters* or *coefficients*. These parameters describe the strength and direction of the relationship between the independent variables and the dependent variable. The true values of these parameters are unknown and therefore their values will be estimated based on sample data. The values of X_1, X_2, and X_3 are specific to each firm and therefore are known and do not have to be estimated. For example, X_1 represents population in each firm's immediate vicinity. This value will be unique to each firm depending on the firm's location. The coefficients, however, are constants for the entire universe of such firms.[4]

Once we have decided on an appropriate theoretical model, the third step in performing a regression analysis is to collect the

4. Of course, we do not live in a linear world. But in many instances, a linear approximation for a nonlinear relationship is quite satisfactory. When it is not, nonlinear estimation methods can be used. Nonlinear models are mathematically more complex but have the

relevant data. We have specified a clear algebraic relationship between sales revenue (S), our dependent variable, and a set of independent variables (X_1, X_2, X_3). Now we must turn our attention to gathering data. We require observations on S, X_1, X_2, and X_3. Data sources, of course, will vary from case to case. In many instances, company records can be utilized for important economic variables such as sales, prices, output, employment, production capacity, salaries and wages, and the like. Data on population, age distribution, ethnicity, wealth, and other economic and demographic factors can be obtained from public sources or from private data collection services. In some cases, the data must be constructed from market transactions. In any event, one should obviously record the data accurately and use common appropriate measurements. For example, any monetary values recorded at different points in time should be converted to real dollars by adjusting for inflation. Errors in recording and measuring data can undermine even the most carefully constructed models.

The fourth step is to apply the regression technique to the model and the data for this particular case. Just how one goes about this will be examined in the next Subparagraph. In the fifth step, one must interpret the results of the analysis, determine their reliability or statistical significance, and apply them to the problem of damage estimation. This is the point of the entire empirical effort — to draw inferences from the sample data. We examine steps four and five in the next Subparagraph through an example.

394b. **Developing the regression model.*** Suppose that the plaintiff has been foreclosed from selling the proverbial widget. Because it expects to win its antitrust case and, furthermore, expects to resume selling widgets following the judgment, the plaintiff wants to estimate the profits that it lost in the past as a result of the foreclosure. One procedure for doing this is to estimate the lost sales revenue and then deduct the avoided costs (i.e., the costs not incurred because the sales were not made) to yield the lost profit. As a first step, then, the plaintiff will be required to estimate its lost sales revenue. Because we do not know what the plaintiff's sales would have been, one way to do this is to examine

same conceptual foundation, strengths, and weaknesses as the linear example explained here.

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the economic performance of other, similarly situated widget vendors and draw inferences about the sales lost by the plaintiff.[5] Regression analysis is a useful tool because it helps us in estimating sales for the plaintiff using the factors that determine sales for other vendors that need not satisfy the demanding standards of the yardstick model. In other words, we do not have to find a clone of the plaintiff. Instead, the plaintiff can use evidence from a sample of firms and statistically control for differences between the plaintiff and the firms in the sample. To this end, we shall estimate the relationship between sales and certain economic and demographic variables for other widget vendors. We can then employ the specific characteristics of the plaintiff along with the estimated relationship for vendors generally to infer the plaintiff's lost sales. The details of this procedure are explored below.

Suppose that experience has shown that widget buyers are drawn largely from those people who live within a three-mile radius of the store. As a result, we are interested in the economic and demographic characteristics of the population within a three-mile ring around each location. For purposes of illustration, we begin with a very simple model in which there is only one independent variable. Specifically, our model describes sales as a function of the total population within a three-mile ring surrounding each store location.

We select for analysis a random sample of 30 widget vendors who were not affected by the alleged violation.[6] The widget manufacturers provided data on sales, while population data were extracted from Census Bureau data files. These data are listed in Table 1 and are depicted graphically in Figure 1. Each point in Figure 1 represents a widget vendor and reflects the population within a three-mile ring and the sales at that vendor's location.

5. This approach to damage estimation is an econometric version of the yardstick model. See ¶391f. For an expanded development, see Roger D. Blair & Amanda K. Esquibel, *Yardstick Damages in Lost Profit Cases: An Econometric Approach*, 72 Denv. U. L. Rev. 113 (1994).

6. A *random* sample is one that is drawn in such a way that every member of the population has an equal chance of being selected. When a sample is not random, the subsequent analysis is vulnerable to the criticism that the results are biased or even contrived.

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TABLE 1
Population and Sales Revenue Data

Store	Population	Sales Revenue ($ in thousands)
1	184,797	$2,039
2	208,971	$2,582
3	74,170	$1,748
4	137,359	$1,745
5	157,489	$1,259
6	60,067	$1,545
7	171,064	$1,680
8	211,457	$1,961
9	50,094	$600
10	201,405	$1,758
11	198,908	$2,320
12	62,246	$1,078
13	76,538	$1,073
14	150,426	$2,149
15	108,818	$1,877
16	124,386	$1,306
17	102,295	$1,509
18	117,102	$1,900
19	99,955	$1,312
20	85,880	$893
21	103,311	$1,438
22	135,663	$1,448
23	215,710	$2,631
24	68,948	$1,168
25	85,287	$1,560
26	217,375	$2,357
27	124,896	$1,818
28	85,110	$1,324
29	55,710	$1,268
30	94,236	$1,375

For the 30 stores sampled, the average sales revenue was calculated as $1,624,000. Based solely on this information, the best estimate of sales revenue for the plaintiff in a "but for" world would be $1,624,000. But a visual inspection of Figure 1 suggests that sales tend to rise as population increases. Obviously, the relationship is not precise because the actual observations are scattered, but there is an unmistakable positive relationship between

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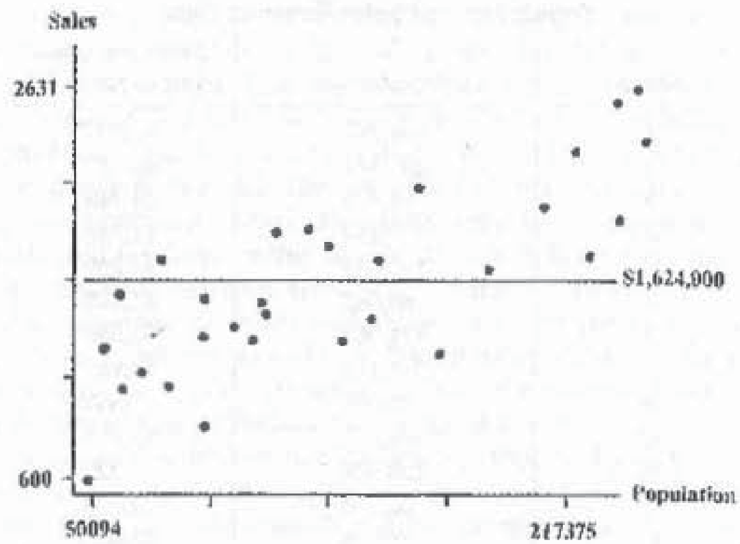


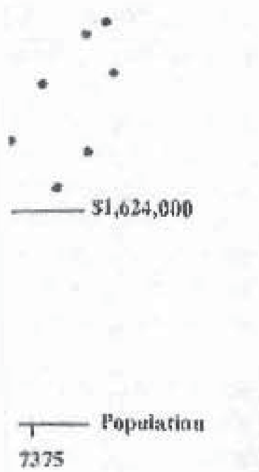
Figure 1

sales revenue and population. This suggests that we may be able to find a better estimate of the plaintiff's "but for" sales than the simple average of the sample. In other words, we may be able to do better if we control for the influence of differences in population.

Sales revenue depends on the number of widgets sold. People demand widgets and the more people there are, the more widgets a vendor will sell. Thus, the economic theory tells us that sales revenue is a function of population in the vendor's location. Each store's sales revenue is positively related to the surrounding population. We will employ a linear approximation of the relationship between sales and population:

$$S = \beta_0 + \beta_1 X_1 + \varepsilon$$

where S represents sales revenue, X_1 represents population within a three-mile ring around a vendor's location, and is a random (stochastic) disturbance (or error) term. In this specification, sales revenue has a nonstochastic component, $\beta_0 + \beta_1 X_1$, and a stochastic component, ε. Here, β_0 and β_1 are the parameters of the model. The coefficient, β_0 is the level of sales that would occur if the population within three miles was zero. For this reason, β_0 is known as the intercept. β_1 is the slope parameter, which explains the



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relationship between X_1 and S, holding all other factors constant. In this case, β_1 is the change in sales revenue given a one-unit increase in the surrounding population.

The nonstochastic portion is composed of the intercept and the independent variable that we expect will explain S.[7] The stochastic portion of the equation is the *unexplained* portion of S and is consequently referred to as the *error*. The inclusion of ε is an explicit recognition that a precise relationship between sales and population is unlikely in real life. In other words, it is unlikely that we can completely explain sales using our independent variable. While our model says that population is the major determinant of sales, we recognize that there are other variables that have relatively minor effects on the dependent variable. The effect of these minor influences is captured by the error term — that is, the random error incorporates these minor factors in the regression model. In this particular example, all other factors are assumed to be unobserved and therefore are contained within the error term. Otherwise, if we could observe these factors, they would be included in the model as additional explanatory variables. It is assumed that the cumulative impact of these minor factors is small relative to the influence of the independent variable that is included. Moreover, it is assumed that these influences can be treated as though they occurred by chance. Problems can arise in regression analysis if important variables are not included. A discussion of omitted variables and omitted variables bias is provided in Subparagraph 394g2.

Incorporating the random error term in the regression equation makes the model probabilistic rather than deterministic. This means that S cannot be predicted exactly, but we can make certain probabilistic statements with measurable degrees of confidence.[8] Regression analysis requires certain statistical assumptions about the error term.[9] The validity of these assumptions may be affected by both the characteristics of the regression model and the data.

7. In models with multiple explanatory variables, the nonstochastic portion includes all of the variables that economic theory indicates are relevant to the determination of the dependent variable.

8. The term "degrees of confidence" is a measure of just what it sounds like: one's confidence in a model or the reliability of that model.

9. This development follows Jan Kmenta, Elements of Econometrics (2d ed. 1986), and G.S. Maddala, Introduction to Econometrics (2d ed. 1992). There are three statistical assumptions implicit in regression analysis regarding the error term that are necessary for the model. If any of these assumptions are suspect, then the value of the regression model is undetermined. First, we assume that the expected value of the random error is zero:

$$E[e] = 0$$

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394c. Estimating the regression parameters. The regression model has been specified as a linear equation,

$$S = \beta_0 + \beta_1 X_1 + \varepsilon.$$

We have collected data on sales and population for a sample of 30 stores. Now we want to use the regression technique to estimate the parameters β_0 and β_1, which we do not know, such that the resulting equation fits the data better than any other straight line. This requires a standard for what constitutes a best fit. The usual concept is that of *least squares*. This process is usually referred to as "ordinary least squares" regression, or OLS. In Figure 2, the least squares regression line is plotted along with the 30 observations. As one can readily see, few observations lie exactly on the estimated line. But the ordinary least squares line is the line of best fit, meaning that it fits the data better than any other straight line. If we were to measure the vertical distance between the observed value of S and the predicted value of S shown as the regression line, we would have a deviation. In other words, the deviation is

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where E is the expectations operator, which denotes the expected value of the bracketed term that follows it. The expected value is a weighted average of the possible values of the variable where the weights are the probabilities. The equation means that if we took repeated samples, the random error term for any particular value of X_1 is on average zero — that is, it washes out on average. This is extremely important because if the expected value of the error term were not zero, then changes in X_1 would be related *systematically* to changes in ε, and the model would not really explain variations in S.

The second assumption about the random error term is that its probability distribution is *normal*. A normal probability distribution has the majority of the values distributed close to the mean value. Normality of the error term means that for every value of X_1, the random error is distributed normally around its mean value, which we just assume equals zero. The normal distribution is continuous, symmetric, and completely determined by two parameters, its mean and its variance. The variance of a probability distribution is a measure of its dispersion. The square root of the variance is the standard deviation. The normality assumption is less restrictive than one would initially think. Recall that the error term accounts for a large number of small influences that are not explicitly included in the model. Each of these minor influences produces a small deviation of S from the value that it would assume if the relationship between X_1 and S were completely deterministic. It turns out that an interesting statistical result is that such random *unsystematic* errors tend to be distributed normally. Normality of the error term is an extremely useful property because it makes precise probability statements about the regression results possible.

The third assumption is that the error terms are homoskedastic, which simply means that every random error has the same (albeit unknown) variance. In our example, this means that the variance of the error term is not larger for areas with higher populations than for areas with smaller populations. This assumption is very important because regression analysis is a form of averaging that deals with small random deviations in an efficient way provided that they are independent. If the random errors are not independent, then something should be done explicitly to deal with this. If the assumption of homoskedasticity is invalid, then the random error terms are said to be heteroskedastic. This causes some statistical problems that can be resolved by using other estimation methods. For an explanation and some nice examples, see Kmenta, Elements of Econometrics 269-98 (2d ed. 1997).

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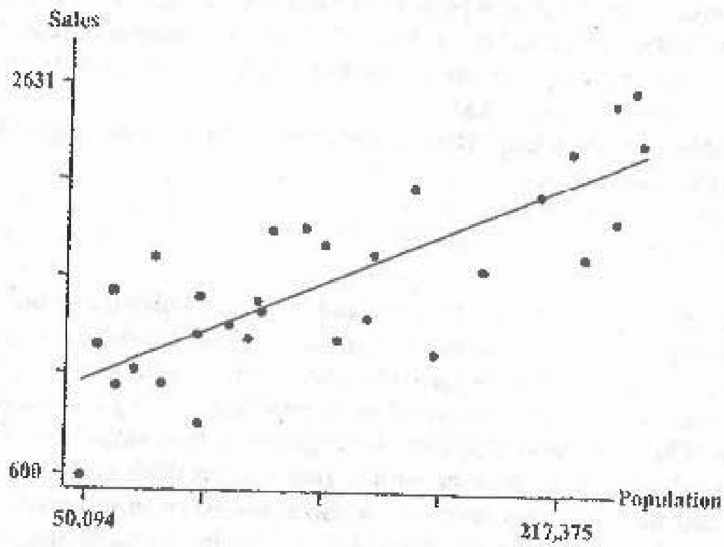

Figure 2

$S - \hat{S}$, where $\hat{S}$ is the predicted value for S based on the regression line. By construction, some of the observations lie above the line while others lie below the line. The sum of these deviations will be zero — that is, the pluses and minuses net out. To avoid this problem and provide a standard of best-fit, we look at the squared deviations rather than the absolute deviations. If we were to compute the squared deviation for each observation and sum them, the resulting total would be smaller than for any other straight line. It is in this sense that the regression line provides a best fit to the data.

For the data in Table 1, the estimates of β_0 and β_1, which are denoted as $\hat{\beta}_0$ and $\hat{\beta}_1$, respectively, are as follows:

$$\hat{\beta}_0 = \$724{,}479 \text{ and } \hat{\beta}_1 = \$7.16.$$

In Figure 2, the regression line that best fits the data has been plotted along with the actual observations. The intercept on the sales revenue axis is $724,479, which is the estimated value of β_0 (or $\hat{\beta}_0$). The slope of the line is the estimated value of β_1 (or $\hat{\beta}_1$). In this case, β_1 is estimated to be 7.16. This means that each store earns sales revenue of $724,479 plus $7.16 for each person who lives within a three-mile radius of the store. If a particular location had 150,000 people within three miles, one would predict a base

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sales revenue of $724,479 plus $7.16 times 150,000, which amounts to $1,074,000, for a total of $1,798,479. There are statistical tests that provide information on the reliability of estimates such as these. We turn to these tests next.

394d. **Evaluating the estimates.** When the regression model is specified as

$$S = \beta_0 + \beta_1 X_1 + \varepsilon$$

the implicit hypothesis is that the population within three miles of the widget vendor is what determines sales revenue. In other words, the hypothesis is that the coefficient β_1 is not zero. In the previous section, we estimated the coefficient on X_1 as a positive value. The estimated slope of the regression line was 7.16, which means that each additional person in the surrounding population will add $7.16 to sales revenue. Although the estimated coefficient is certainly not zero, the estimate could be imprecisely measured or spurious — that is, the true coefficient could be zero even though our calculation provides a positive coefficient. This possibility arises because the sample could have given us a misleading estimate of the true value of β_1. Rather than just guessing about whether our estimate is reliable, we can test this statistically. Using some basic principles of statistical inference, it is possible to test whether the estimated coefficient is statistically significantly different from zero. In other words, we can test the original hypothesis that X_1 is, in fact, a determinant of sales revenue.

Hypothesis testing. Econometricians specify the hypothesis in two parts. When considering whether a coefficient is "statistically significant," economists usually compare the coefficient to zero. First, the so-called null hypothesis is that the influence of the independent variable is actually zero — that is, that X_1 has no influence on sales revenue. In other words, values of X_1 provide no information on the value of the dependent variable. As a statistical matter, the null hypothesis can be correct even though the ordinary least squares procedure calculates a value for β_1 that is numerically different from zero. Second, the alternative hypothesis is that the independent variable does explain the value of the dependent variable. In other words, the alternative hypothesis asserts that the coefficient is not equal to zero. Thus, the null hypothesis is

$$H_o: \beta_1 = 0$$

and the alternative hypothesis is

$$H_a: \beta_1 \neq 0$$

Interestingly, we actually test the null hypothesis rather than the alternative hypothesis. If the null hypothesis is rejected, then we infer that a statistically significant relationship exists between the independent and dependent variables. In other words, if we reject H_o, we accept H_a, the alternative hypothesis.

The null hypothesis is rejected when the sample data yield results that are sufficiently unlikely if the null hypothesis were true, meaning that we are able to precisely identify a nonnegative effect. In our previous example, the sample data provided an estimate of β_1, which we call $\hat{\beta}_1$, equal to \$7.16. If the true value of β_1 were zero, it is still possible to observe a positive estimate. But is it likely? Since we can never *know* the true value of β_1, we must rely on statistical inference. If it is sufficiently unlikely that we would observe an estimate of β_1 equal to \$7.16 when the true value of β_1 is zero, then we will infer that β_1 is not zero. The null hypothesis will be rejected and, by default, the alternative hypothesis will be accepted.

In order to test the hypothesis that $\beta_1 = 0$, we need a test statistic. To construct the test statistic, we have to introduce the concept of *standard error*. Using our data, we drew a sample and estimated values of the regression coefficients. If we draw other samples and repeat the process, the numerical values of the estimates are bound to be somewhat different. The standard error of, say, $\hat{\beta}_1$ is a measure of how much the estimates of $\hat{\beta}_1$ would vary across different samples. This is a measure of dispersion in the estimated coefficient. Now, under the assumptions of the ordinary least squares model, the difference between the estimate of β_1 (or $\hat{\beta}_1$) and the true value of β_1 divided by the standard error of $\hat{\beta}_1$,

$$\frac{\beta_1 - \hat{\beta}_1}{s(\hat{\beta}_1)},$$

is called the *test statistic*. This statistic has a so-called t distribution with $n - k$ degrees of freedom where n is the number of observations (i.e., the sample size) and k is the number of parameters being

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estimated.[10] In our simple model, n equals 30 and k equals 2. According to the null hypothesis, $\beta_1 = 0$; thus, we will be interested in the ratio of $\hat{\beta}_1$ to its standard error, $\hat{\beta}_1 / s(\hat{\beta}_1)$, which has a t distribution with $n - k$ degrees of freedom.

A brief review of the t distribution will aid our understanding of statistical inference. The t distribution is a symmetric distribution that resembles the normal (bell-shaped) distribution. In fact, as the sample size increases, the t distribution increasingly approaches the normal distribution. As a result, no meaningful precision is lost by using the normal distribution for sample sizes in excess of 30. In Figure 3, we have a graphical representation of the t distribution for the estimate of β_1 under the null hypothesis that $\beta_1 = 0$.

If the null hypothesis were true, then the bulk of the sample values of $\hat{\beta}_1$ will be close to zero. Now, if the sample generates a value of $\hat{\beta}_1$ that is sufficiently far from zero, then we will infer that the true value of β_1 is not zero after all. In Figure 3, we have cut off one-half of 1 percent of the distribution on each tail. Thus, the sum of the two striped areas is 1 percent; the remaining 99 percent is the unstriped area. For 28 degrees of freedom, the critical (or threshold) values are ± 2.763.[11] If, in fact, the null hypothesis $\beta_1 = 0$ is correct, repeated samples of 30 widget vendors will yield values of $\hat{\beta}_1$ and $s(\hat{\beta}_1)$ such that 99 percent of the time the ratio will lie between -2.763 and 2.763. That is, observing $\hat{\beta}_1 / s(\hat{\beta}_1)$ greater than 2.763 or less than -2.763 will be very unlikely if β_1 is really zero.

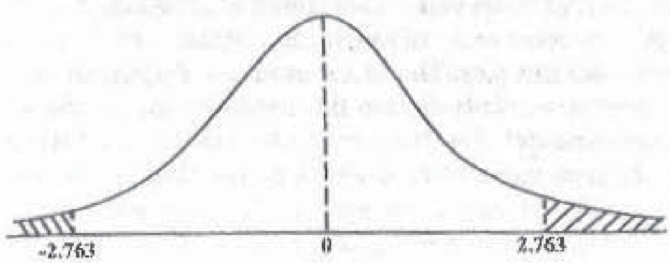

Figure 3

10. This standard statistical result is provided by Jan Kmenta, Elements of Econometrics 244 (2d ed. 1997).

11. The critical t values for various combinations of degrees of freedom and acceptance regions are found in the table of the t distribution, which can be found in any statistics or econometrics text.

A somewhat more general treatment is possible. If we let α represent the level of statistical significance that we will use as a threshold, then we can find boundary values for the acceptance and rejection regions in a table of the t distribution.[12] In particular, the critical values are given by the table as $\pm\, t_{n-2,\alpha/2}$ where $n-2$ reflects the degrees of freedom and $\alpha/2$ reflects the fraction of the t distribution that is in each tail of the distribution. The tails of the distribution, based on the significance level, represent the rejection region. With respect to the null hypothesis that β_1 equals zero, the acceptance region for H_o is generally given by

$$-t_{n-2,\alpha/2} \leq \frac{\hat{\beta}_1}{s(\hat{\beta}_1)} \leq t_{n-2,\alpha/2}$$

Thus, in our example, the acceptance region is determined by

$$-t_{28,.005} \leq \frac{\hat{\beta}_1}{s(\hat{\beta}_1)} \leq t_{28,.005},$$

which results in the acceptance region noted above:

$$-2.763 \leq \frac{\hat{\beta}_1}{s(\hat{\beta}_1)} \leq 2.763.$$

In short, if the sample data provide an estimate of $\hat{\beta}_1$ and a standard error of $s(\hat{\beta}_1)$ such that the value of $\hat{\beta}_1 / s(\hat{\beta}_1)$ falls into the acceptance range, this means that we fail to reject the hypothesis that $\beta_1 = 0$. If we fail to reject the null hypothesis, then the probability of calculating a test statistic outside of the acceptance region is small. In other words, we say that β_1 is *statistically insignificant*.

If the sample generates a value for $\hat{\beta}_1$ and $s(\hat{\beta}_1)$ such that the test statistic is, say, larger than the critical value, then the test statistic is in the rejection region. In other words, the value of the test statistic is incompatible with the null hypothesis. We, therefore, reject the null hypothesis at the α level of significance. When evaluating the regression results, the conventional thresholds for

12. The researcher can select the value of α based on how sure he or she wants it to be: 90 percent, 95 percent, 99 percent.

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the critical probabilities are 5 percent and 1 percent. In our example, we employ a threshold of 1 percent ($\alpha = 0.01$).

In our example, $\hat{\beta}_1 = 7.16$ and $s(\hat{\beta}_1) = 1.03$. Thus, the t statistic is

$$t = \frac{\hat{\beta}_1}{s(\hat{\beta}_1)} = \frac{7.16}{1.03} = 6.95.$$

From the table of the t distribution, the critical t statistics are 2.048 for 5 percent and 2.763 for 1 percent when there are 28 degrees of freedom. Since the t statistic for our example is 6.95, the probability of observing the estimated value of $\hat{\beta}_1$ if, in fact, the true value of β_1 were zero is far less than 1 percent.

Based on the t distribution, the probability of drawing a sample of 30 stores that would generate an estimate as different from zero as the estimate observed when the true value is zero is far below 1 percent. The econometrician cannot say with certainty that the true value of β_1 is not zero, but it can be said that it is extremely unlikely. Thus, one can be quite confident that thepopulation within three miles of the widget vendor is a determinant of sales revenue. We say then that this variable is *statistically significant.*

Confidence intervals. The regression model generates a point estimate of β_1, which in our example is 7.16. In addition to evaluating the significance of the point estimate, we can estimate an interval or range of values between which the true value of β is likely to be found. In other words, we can say with some degree of confidence that the true value of β will be between the two endpoints of the estimated interval. To determine how precise our point estimate may be, one may calculate the so-called confidence interval around the estimate. The confidence interval is a range of values such that we are *confident* — but not absolutely sure — that the true value of β lies within that range. First, we start with the degree of confidence we want, say, 95 percent; that is, = 0.05. Then the estimate of β_1 and its standard error are used to construct the

$$\hat{\beta}_1 - (t_{n-2,\alpha/2})\, s(\hat{\beta}_1) \le \beta_1 \le \hat{\beta}_1 + (t_{n-2,\alpha/2})\, s(\hat{\beta}_1).$$

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Of course, $\hat{\beta}_1$ is our estimate of $\hat{\beta}_1$, $s(\hat{\beta}_1)$ is the standard error of that estimate, and $t_{n-2,\alpha/2}$ can be found in the table of the t distribution. For our example, the 95 percent confidence interval is

$$\$7.16 - (2.048)(\$1.03) \le \beta_1 \le \$7.16 + (2.048)(\$1.03),$$

or

$$\$5.05 \le \beta_1 \le \$9.27.$$

We cannot say with certainty that the true value of β_1 lies between \$5.05 and \$9.27, but we can make a probabilistic statement. In particular, one can say that the probability that the confidence interval includes the true value of β_1 is 95 percent.

Thus, while our point estimate is \$7.16, the lower and upper bound on the 95 percent confidence interval are \$5.05 and \$9.27, respectively. As a result, one can be fairly confident that an additional person within a three-mile radius will raise sales revenue by a positive amount, somewhere between \$5.05 and \$9.27.

Goodness of fit. Finally, there is another way to evaluate how well the regression model explains the observed data. This is the coefficient of determination, which is usually denoted by R^2. This measure is calculated by breaking down the variation in the dependent variable (S) into its component parts and isolating the proportion of the variation accounted for by the independent variable (X_1).[13] The R^2 is a measure of the goodness of fit as it represents the proportion of the variation in sales revenue that the model explains. In this example,

$$R^2 = 0.633,$$

13. As a general matter, the confidence interval for the estimate of $\hat{\beta}_1$ is

$$\hat{\beta}_1 - t_{n-2,\alpha/2} s(\hat{\beta}_1) \le \beta_1 \le \hat{\beta}_1 + t_{n-2,\alpha/2} s(\hat{\beta}_1)$$

where $t_{n-2,\alpha/2}$ is the value of a t statistic with $n-2$ degrees of freedom and that cuts off α of the area under the t distribution at each tail. Notice that in this expression the end points are random variables because $\hat{\beta}_1$ appears. As a result, we can make the following sort of probabilistic statement: If one takes repeated samples and calculates confidence intervals in the same fashion, then $(1 - \beta)$ percent of those confidence intervals will enclose the true parameter value of β_1. The smaller the confidence interval, the more precise the estimate. Since R^2 is a proportion, it must assume valuesbetween zero and one.

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which means that the variation in population across the 30 vendor locations explains just over 63 percent of the variation in sales revenue across those locations. Whether this is good or bad depends on expectations. For a simple model like ours, one might consider this to be a rather good performance. On the other hand, the model leaves nearly 37 percent of the variation unexplained. An R^2 value can often be rather low, especially with cross-sectional data. But preoccupation with indiscriminately "improving" the R^2, as some literature may unintentionally encourage, can be inconsistent with objective analysis.[14]

Correlation versus causation. Even though regression analysis relates a dependent variable to one or more independent variables, it is important to keep in mind that this relationship does not imply *causation*. Regression results may suggest that one variable is related to or correlated with another, but this does not translate directly into a causal effect. In other words, we cannot necessarily infer that the independent variable causes some effect on the dependent variable. Causation must be based on some justification rooted in economic theory. Regression alone cannot satisfy the requirements for proving causality. Rather, regression analysis enables us to empirically test a hypothesis based on what economic theory would predict. This is important to keep in mind when interpreting regression results, inferring the effects of alleged anticompetitive conduct, and making statements about damage estimates.

394e. Statistical properties of least squares estimators. Under the assumptions of the least squares regression model, the resulting estimates have some desirable statistical properties.[15] First, the estimates of β_0 and β_1 are *unbiased*. In statistical terms, bias has nothing to do with prejudice or favoritism, but bias is still undesirable. If an estimate is unbiased, it means that the expected value of the estimator is equal to the true value of the population parameter. This is comforting because the sample data are only a subset of the population. In our case:

14. For example, Glen A. Stankee, *Econometric Forecasting of Lost Profits: Using High Technology to Compute Commercial Damages*, 61 Fla. B.J. 83, 85 (1987), writes "the higher the R-squared factor, the more reliable the predictions will be." But the R^2 can be inflated by simply adding more explanatory variables (even unrelated ones) to the regression model, which encourages a "kitchen sink" approach to modeling. As we pointed out above, what should be included in the model is a matter of economic theory.

15. For the technical developments of these properties, see Jan Kmenta, Elements of Econometrics (2d ed. 1997).

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Unbiasedness is a desirable property because it means that the least squares estimators are close, on average, to the true population parameter. If we had a biased estimator, then on average the estimate would not reflect the true population parameter.

Second, the least squares regression estimators have a smaller variance than any other linear, unbiased estimators. In this sense, these estimators are deemed "best." In combination, these two properties define *efficiency*. If the estimator is unbiased and the variance of the estimator is smaller than the variance of any other unbiased estimator, then the estimator is said to be efficient. Third, the least squares regression estimators are *consistent*, which means that as the sample size increases, the bias (if any) approaches zero and the variance approaches zero. In other words, as the sample size increases, our estimates will come closer and closer to the true value of the parameter. Taken together, these properties are reassuring. Given that we are forced to draw inferences at all, these properties suggest that inferences based on our regression analysis are about as good as one could expect.

394f. Multiple regression. In our illustrative example, one may object that the model is too simplistic because there is only one explanatory variable, population within three miles of the vendor location. One might feel that other variables, such as income, wealth, racial composition, educational attainment, advertising, presence of competitors, and the like could also be important in determining total sales revenue. This possibility cannot be ignored on a priori grounds unless economic theory suggests that these other variables should not be included. Accordingly, we return to the first step in the regression analysis, which involves the use of economic theory to identify the relevant economic and demographic variables to include in the model.

As we concluded earlier, sales are dependent on the local population and therefore we included the population within a three-mile ring around each vendor location. In addition to the sheer size of the population, other characteristics of the population may be relevant. For example, sales may also be influenced by the income and wealth of the surrounding population. Accordingly, one may want to include measures of household income, per

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capita income, or a wealth measure such as the value of housing in the area. Further, female workforce participation rates may influence sales as well. To the extent that educational attainment is important in the decision to buy a widget, we may want to include variables for median educational attainment in years or the percentage of the population that graduated from college. If racial composition seems important on a priori grounds, one can include a variable indicating the percentage of the total population that is a given race. One could also include a measure of advertising and other promotional expenditures. Finally, the presence and degree of competition can also be included in the regression model.

When we employ a more complete model by adding other independent variables, plotting the resulting relationship on a two-dimensional graph becomes impossible. The concept, however, remains the same: fitting a linear relationship to observations that are not precisely linear due to random errors. The expanded model may look like the following:

$$S = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \varepsilon$$

where S represents annual sales revenue, X_1 is total population within a three-mile ring, X_2 is per capita income, X_3 is the median value of housing, X_4 represents the amount that each vendor spent on advertising, X_5 denotes the number of competitors faced by each vendor, X_6 tells us whether the vendor location is in a shopping mall, and ε is the random error term. In order to estimate the regression parameters — that is, the various β coefficients, one must gather data on each of these variables for every vendor location in the sample. In the case of whether the store is in a mall or not, a particular vendor is either in or not in a mall. We can therefore indicate whether a particular location is a mall location by assigning a value of 1 if a vendor is in a mall and a zero if it is not. Variables that take on a value of one or zero are called binary or dummy variables. The interpretation of the coefficients in multiple regression is slightly different. One infers that *after controlling for the other variables in the regression*, a one-unit change in the variable under consideration is associated with a change in sales equal to the coefficient. For the binary case, the coefficient yields the level of sales attributed to being in a mall rather than not being in a mall, holding all other factors constant.

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Similarly, an expert could also use dummy variables to measure the effects of geography or time. Geographic indicators are often used to capture time-invariant effects that geographic areas (e.g., state or MSA-level dummy variables) have on the dependent variable. Experts also use year indicators to capture the effects of time that are common to all the observations used in the analysis. For example, for an analysis that encompasses 2010 to 2014, an expert could include dummy variables representing 2011, 2012, 2013, and 2014, omitting the variable representing 2010. The interpretation of the coefficient on the 2011 variable would indicate the effect of the year 2011 on the dependent variable relative to the omitted year, 2010.

394g. **Vulnerability of regression analysis.** Regression analysis may be vulnerable to attack in damage cases on several grounds; this Subparagraph illustrates only two. First, the very essence of statistical inference may be attacked. Given the history of statistical inference in litigation, it will be difficult to challenge the concept, but the methods employed by the expert are apt to be fair game. Second, one may challenge regression results on the basis of model specification errors, including omitted variables as well as other misspecifications. For analysis of a specific example where regression analysis was used improperly, see Subparagraph 399c for a discussion of the *Conwood* damage estimation.

394g1. Nature of statistical inference. Statistical analysis generally and econometrics in particular have been used quite often in litigation. Nonetheless, the seemingly mysterious nature of statistical inference can be a handicap in front of a jury. The expert cannot make unqualified statements. Every contention is probabilistic in nature and therefore can appear somewhat speculative. For example, suppose the coefficient on per capita income in the multiple regression equation is statistically significant at the $\lambda = 0.05$ level. As we discussed above, this means that the probability of observing an estimate of the observed magnitude if the true relationship were zero is quite small. More specifically, the probability of drawing a sample of 30 vendors that would produce an estimate of β_1 that is this different from zero when the true value is zero is less than 5 percent. As a consequence, the econometrician will be reasonably confident of this result, but he or she cannot say with certainty that there is no chance that the true impact of changes in per capita income is in fact zero. Under persistent cross-examination, the econometrician

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must concede that there is a positive probability that the observed results may be imprecise or spurious.

394g2. Specification error. Specification error may occur when the econometrician fails to construct a sound *economic* model at the outset. This may arise (1) when a relevant explanatory variable has been omitted or (2) when an irrelevant explanatory variable has been included. Specification error also may occur due to *mathematical* misadventures — that is, (1) when an incorrect mathematical form of the regression equation has been selected or (2) when the disturbance term has entered the regression equation in an incorrect way. These problems are examined below.

Omitted variables. Suppose that an important explanatory variable has been left out of the model because, for example, the expert was unaware that the omitted variable was an important determinant of the dependent variable.[16] The omission of a relevant explanatory variable may make the estimates of the other variables biased. This, of course, sounds ominous, but bias in a statistical sense means only that the expected value of the estimate is not equal to the true population parameter. But for the purposes of damage estimation, this means that omitted variables could bias the damage estimates either up or down.

Due to the nature of econometric models, it will be difficult for an econometrician to maintain that there is no possibility of having omitted an economically significant explanatory variable. Consequently, he or she must concede that omitted variable bias may be present. But economic theory can be used to explain the choice of the variables that are included in the model. Although one can never fully rule out the possibility of omitted variable bias, the expert can take steps to ensure the most inclusive model possible according to economic theory.

Consider our regression model for estimating sales revenue at a widget vendor's location. Our estimate is based on a sample of 30 stores. These are located in 30 different places around the country. We have not included any variable to account for climatic variations across locations. Additionally, it is undeniable that the skills and abilities of a manager can make a difference in a vendor's success, but we do not have a variable that controls for such differences across the sample. The list of possibly relevant, albeit omitted, explanatory variables goes on and on.

16. Alternatively, he or she may have left it out because no data on that variable were available.

Including irrelevant variables. Some experts may adopt a "kitchen sink" approach and include every conceivable variable in the regression equation with little (if any) theoretical justification. As it turns out, this specification error does not result in biased estimators. Consequently, this specification error just adds clutter, but it does not do any real harm. Variables included in the model, however, should be based on sound economic theory and have some hypothesized prediction. Use of economic theory when selecting variables to include in the model should help to avoid including irrelevant variables.

An expert could run into trouble if he or she uses the kitchen sink approach and employs variables that capture the same type of relationship. For example, assume the expert thought that household income in the surrounding area was an important determinant of some dependent variable. If the expert uses the median household income in conjunction with per capita income in the area, then each of these coefficients might be capturing the same effect in the model. In other words, there could be a high degree of correlation between these two proposed independent variables. In situations like this, the expert should select the most appropriate measure to estimate the variable that economic theory would predict to be important.

Nonlinear versus linear models. Most regression models have a linear mathematical specification.[17] It may be true that the correct specification is nonlinear and the linear model is just an approximation of the correct model. In that case, it is easy to show that the linear model fails to include the relevant higher order variables. For example, it may be true that the age of a business — that is how long a company has been in business, may influence sales revenue. Age of a business and sales revenue are likely positively related. If it is true that age is linearly related to sales revenue, then for each additional year in business the company would realize some unit increase in sales revenue. It is possible, however, that the age of the business only matters linearly up to a point and then matters less and less. Hence, decreasing returns to age are introduced. If the expert thinks that this might be the case, then age of the business squared should be included. If the sign on the squared term is negative and the coefficient is statistically significant, then this would imply that age of the business is positively related to

17. Log-log model specifications are also popular because the coefficients represent elasticities.

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sales revenue, and at some point the increase in sales revenue increases at a decreasing rate. This is an example of a nonlinear relationship. Accordingly, omission of such a term if relevant could mean that the model is misspecified.

Nonlinearity could also enter a regression model when using logarithms. Use of a logarithm of the dependent variable transforms a continuous coefficient to a percentage change rather than a unit change. This is different from a linear slope coefficient because the relationship between an independent variable and the dependent variable is no longer constant. In this way, the line of best fit is no longer strictly linear in nature. In our example relating sales revenue to the surrounding population, we could use the natural logarithm of sales instead of sales itself. If this transformation is made, the coefficient on the surrounding population would be interpreted as a percentage change. If the coefficient on the surrounding population were estimated to be 0.10, then we would multiply the coefficient by 100 and say that a 1 percent increase in the surrounding population is associated with a 10 percent increase in sales revenue. Use of logarithms, therefore, is an example of a nonlinear transformation.

Incorrect specification of the disturbance term. It is possible that specifying an additive disturbance term (ε) is incorrect and that it should enter the regression equation in, say, a multiplicative way. This error can also yield biased estimators.

394g3. *Autocorrelation.* The statistical problems associated with autocorrelation may surface when the expert relies on time series data. For example, when using monthly sales data over, say, a five-year period, it would be desirable for the disturbance terms to be independent. Since economic variables tend to be nonrandom, however, the effect of the omitted variables that give rise to the error term in one period may carry over to the next period. When this is the case, the disturbance today will influence the size of the disturbance tomorrow.

It can be shown that the usual regression analysis yields unbiased estimators even when autocorrelation is present. This, of course, means that the expected value of the estimator will be equal to the population parameter even when autocorrelation is present. In other words, on average, the estimate will be correct. But it turns out that the estimated variances (and, therefore, the standard errors) are biased. If monthly sales data are positively correlated, then the bias will be negative. This in turn distorts the

tests of statistical significance. One is more likely to infer mistakenly that a coefficient is statistically significant. Fortunately, there are statistical methods for dealing with this problem.

394g4. Data collection and measurement problems. A regression model may be undermined considerably merely by human error in recording data. Data collectors may simply write down the wrong values or may not understand what the recorded values signify. Another common mistake is a failure to take collected data and transform them into common measurements. For example, if *annual* advertising expenditures are recorded from one location, then *annual* advertising expenditures must be recorded for all locations. It would distort the analysis if *quarterly* data were inadvertently included for several locations. Moreover, it is helpful if the data span the same time period. If some observations are on a calendar year basis while others are on fiscal year basis, exogenous economic factors (those the model assumes to be constant) could distort the analysis.[18] For these reasons, it is important to check the data for errors or outliers (i.e., an observation that is very different from most other observations). If errors are detected in the data, they should be corrected. If correction is not possible, then the expert should consider removing the errors. If outliers are detected, the expert should test the sensitivity of the main analysis by comparing it with a model that excludes the outliers. A robust model would not be sensitive to small changes (e.g., the removal of one outlier).

¶395. Damages in Overcharge Cases

Antitrust plaintiffs may complain about overcharges — prices that are higher than they would otherwise be — as a result of illegal monopolization, a price-fixing conspiracy, an illegal merger, or an illegal vertical restraint such as tying, exclusive dealing, or resale price maintenance.[1] An immediate question is what the measure of

18. It is possible to control for these exogenous factors, but one must be sure to do so if data are drawn from different time periods. In addition, this makes the analysis more complicated.

¶395. n.1. When buyers collude, the claim will involve prices that are too low — that is, undercharges. These cases will also be examined in this Paragraph. On buyer cartels, see Subchapter 20B; *and see* Roger D. Blair & Jeffrey L. Harrison, Monopsony in Law and Economics 36-54 (2010).

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damages should be in an overcharge case. There are two obvious alternatives: (1) lost profits and (2) the overcharge, which is the difference between the price actually paid and the price that would have been paid "but for" the unlawful conduct multiplied by the quantity purchased. As we will see in the next Subparagraph, these measures of damages are not economically equivalent.

What has come to be known as the overcharge measure of damages received early approval from the Supreme Court. In *Chattanooga Foundry*,[2] the manufacturers of cast-iron water pipe had been engaged in a price-fixing conspiracy. The city of Atlanta had purchased some of that pipe for use in its municipal waterworks at the collusive prices. The city suffered no lost profits because by definition not-for-profit entities have no profit to lose. The Court, however, found that the city ". . . was injured in its property, at least, if not in its business of furnishing water, by being led to pay more than the worth of the pipe."[3] As a result, the Court found that the city could recover damages for "the difference between the price paid and the market or fair value" of the pipe that it had purchased. This measure of damages was clearly appropriate in *Chattanooga Foundry*, given the not-for-profit nature of the city's undertaking. The direct loss caused by the price fixing cartel was the increased cost of providing the water service above the cost at which it could have been provided had pipe prices been competitively determined. In the case of for-profit businesses, however, it is not as easy to conclude that the overcharge is the appropriate measure of damages. Section 4 of the Clayton Act provides for the recovery of threefold the damages actually *sustained*. This is not necessarily captured by the overcharge, as we shall see below. The most accurate measure of the damages actually sustained is lost profit, but this will usually lead to smaller recoveries and therefore is not apt to be selected by plaintiffs if they are given a choice.

395a. Lost profits versus overcharges.[4] According to §4 of the Clayton Act, an antitrust victim is entitled to recover

2. *Chattanooga Foundry & Pipe Works v. City of Atlanta*, 203 U.S. 390 (1906).
3. *Id.* at 396.
4. For an argument in favor of lost profits, see Jeffrey L. Harrison, *The Lost Profits Measure of Damages in Price Enhancement Cases*, 64 Minn. L. Rev. 751 (1980). For an argument in favor of overcharges as opposed to lost profits, see Frank H. Easterbrook, *Treble What?*, 55

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"threefold the damages by him *sustained*."[5] As we shall see, the most commonly used measure of damages, *viz.*, the overcharge, is an ambiguous proxy for the actual damages suffered. Initially, however, we should note that the overcharge measure of damages typically exceeds the unjust gains to the cartel members. This can be seen quite readily in Figure 1. Prior to the formation of the price-fixing cartel, a typical competitive firm will sell a quantity equal to Q_1 at the market-determined price of P_1. The firm earns no excess profit because price equals average cost at that quantity. The proportional demand curve, which is denoted as $d = (1/n)\ D$ in Figure 1, intersects marginal and average cost at the competitive price (P_1) and output (Q_1). Following the formation of a price-fixing cartel, each firm will restrict output to the point where its marginal revenue (*mr*) equals its marginal cost (*MC*) — that is, each firm will reduce output from Q_1 to Q_2. The collusive price will rise from P_1 to the collusive price of P_2, and the cartel members will each earn excess profits equal to $(P_2 - C_2)\ Q_2$.

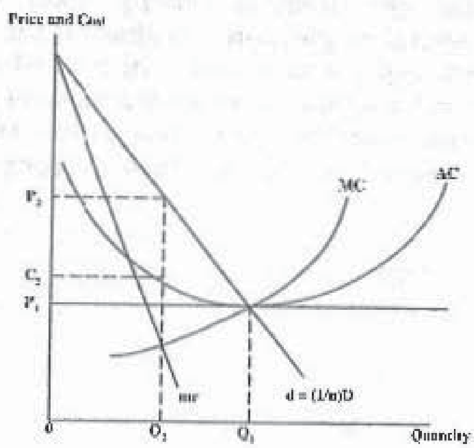

Figure 1

Antitrust L.J. 95 (1986). On lost profit damages when the direct purchaser is an intermediary, see Herbert Hovenkamp, The Antitrust Enterprise: Principle and Execution 72–76, 304–05 (2006).

5. 15 U.S.C. §15(a).

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In contrast to the excess profit, the collusive overcharge will be equal to the difference between the unlawful price (P_2) and the competitive price (P_1) times the actual quantity sold (Q_2):

$$O/C = (P_2 - P_1)Q_2.$$

It is clear that, since C_2 exceeds P_1, the collusive overcharge exceeds the illicit profits earned by the colluding sellers.[6] The difference is due to the inefficient level of output selected by the colluding firms. Consequently, the difference between the profits and the overcharge is borne appropriately by the colluding firms.

For business customers, purchases from the colluders are made in order to conduct their businesses. As a result, the damages sustained are captured most appropriately by their lost profits. Moreover, despite the prevalence of the overcharge as a measure of damages, it is a disconcerting fact of life that the overcharge is not precisely the same as the lost profit. The overcharge may be larger or smaller than the lost profit depending upon the economic circumstances. Several simple examples illustrate this point.

395a1. Overcharging a monopolist. In the first example, suppose that a monopolist produces output at a constant marginal (and average) cost represented by the horizontal line labeled MC_1 in Figure 2. The demand for the product is represented by the

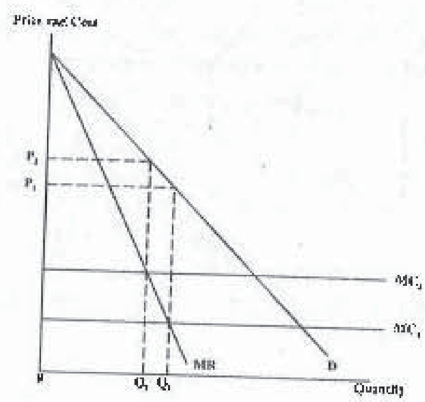

Figure 2

6. All of this analysis assumes that the colluding firms do not cheat, that the cartel members are identical, and that the cartel maximizes industry profits.

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Assume that the firm's formerly competitive suppliers form a cartel and thereby raise the prices of an input needed by the monopolist. As a result of paying higher prices, the monopolist's marginal cost rises from MC_1 to MC_2. This causes the monopolist to reassess its own price and output decisions. Given a marginal cost of MC_2, it is now optimal (i.e., profit-maximizing) for the monopolist to reduce its output to Q_2 and increase its price to P_2.

At the initial price and output, profit was equal to $(P_1 - MC_1)Q_1$, while at the new price and output, the profit has fallen to $(P_2 - MC_2)Q_2$. The lost profit ($\Delta\pi$) is therefore equal to

$$\Delta\pi = (P_1 - MC_1)Q_1 - (P_2 - MC_2)Q_2.$$

The overcharge (O/C) is captured by the increase in marginal cost multiplied by the quantity of output:

$$O/C = (MC_2 - MC_1)Q_2.$$

In this case, some algebraic rearrangement reveals that the lost profit exceeds the overcharge.[7]

A numerical example.[8] We can provide a numerical example that corresponds to the graphical analysis. Suppose that the demand function assumes thefollowing simple form:

7. We need to show that

$$\Delta\pi > O/C, \text{ i.e., } (P_1 - MC_1)Q_1 - (P_2 - MC_2)Q_2 > (MC_2 - MC_1)Q_2$$

or

$$(P_1 - MC_1)Q_1 - P_2Q_2 + MC_2Q_2 - MC_2Q_2 + MC_1Q_2 > 0$$

or

$$(P_1 - MC_1)Q_1 - (P_2 - MC_1)Q_2 > 0.$$

The first term on the left-hand side is the maximum profit obtainable by operating where marginal cost (MC_1) equals marginal revenue. The second term is the profit associated with producing a quantity below that at which marginal cost (MC_1) equals marginal revenue. Thus, the first term is necessarily larger than the second,and therefore the lost profit exceeds the overcharge.

8. The interested, albeit mathephobic, reader can omit this example without loss of continuity or can simply read around the technical material.

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$$P = 100 - 0.01Q,$$

where P denotes price and Q represents quantity. The monopolist's total revenue is the product of price and quantity:

$$TR = PQ = 100Q - 0.01Q^2.$$

Marginal revenue[9] equals 100 – 0.02Q. In the "but for" world, the monopolist's marginal (and average) cost is assumed to be constant at $4. Now, the maximum profits that the monopolist can earn require producing where marginal revenue equals marginal cost:

$$100 - 0.02Q = 4$$

Solving for the optimal quantity yields $Q = 4800$, and substituting that quantity into the demand function yields a profit-maximizing price of $P = \$52$. The firm's profit ($\pi$) can be found by substituting into the profit function:

$$\pi = 100Q - 0.01Q^2 - 4Q.$$

In this case, the maximum profit is $230,400.

Now suppose that the firm is overcharged due to a price-fixing conspiracy and marginal cost rises from $4 to $8. Since there is no reason for the demand function to change, the firm's marginal revenue will not change. Once again, the firm will maximize its profit by producing the output where marginal revenue equals marginal cost:

$$100 - 0.02Q = 8$$

Solving this condition for Q, it follows that the optimal quantity falls from 4,800 to 4,600 units. Substituting a quantity of 4,600 into the demand curve reveals that the corresponding price will rise to $54. By substitution into the new profit function, $\pi = 100Q - 0.01Q^2 - 8Q$, we find that profit is now $211,600. The lost profit is the

9. Marginal revenue is the first derivative of total revenue:
$$MR = \partial TR/\partial Q = 100 - 0.02Q.$$

difference between the actual profit following the illegal behavior of \$211,600 and the "but for" profit of \$230,400 — or \$18,800.

The overcharge is the difference between the actual price of \$8 paid and the "but for" price of \$4 times the units purchased, which is 4,600. Accordingly, the total overcharge is (\$4)(4,600) = \$18,400, which is less than the lost profit. As a result, the overcharge damages will undercompensate the antitrust victim relative to a lost-profits calculation.

395a2. *Overcharging competitors.* When the cartel overcharges competitive firms, the results are somewhat different. Suppose that each unit of the competitively produced output requires one unit of an input that the cartel supplies. The increase in the price of that input will cause the firms' average and marginal costs to rise by the amount of the overcharge. The effect on the profits of the overcharged firms will depend on what happens to the price, which is governed by supply and demand conditions.

In Figure 3, the competitive firm initially had average and marginal cost curves AC_1 and MC_1, respectively. At a competitive price of P_1, the firm maximized its profit by producing where price was equal to marginal cost — that is, at a quantity of Q_1. As Figure 3 reveals, the competitive firm sold Q_1 at the competitive price and earned a competitive return in doing so.[10] The influence of the cartel overcharge is to shift the average and marginal cost curves from AC_1 and MC_1 to AC_2 and MC_2, respectively. The effect on profit will depend on what happens to price.

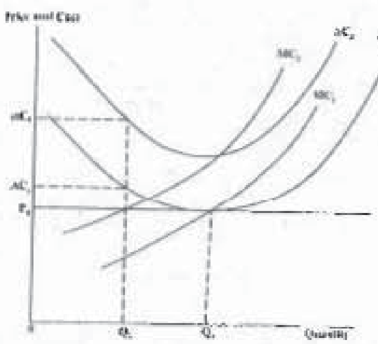

Figure 3

10. Although price equals average cost at Q_1 and the competitive firm's profits are zero, the firm still earns a competitive return on its investment because that is part of the cost. In other words, the average cost curve has embedded within it a competitive return.

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At one extreme, suppose that the price does not rise at all. The competitive firm in Figure 3 will respond to the higher cost by producing that quantity where MC_2 equals P_1 — that is, it will produce Q_2. In this case, the firm's lost profit will be equal to the loss that it experiences, which equals $(C_2 - P_1)Q_2$. The overcharge, however, is equal to the increase in average cost times the quantity purchased: $(C_2 - C_1)Q_2$. Now, one can see by inspecting Figure 3 that the lost profit exceeds the overcharge. Thus, the overcharge estimate does not adequately compensate the antitrust victim in this case.

At the other extreme, we may assume that the competitive price rises by the full amount of the overcharge. In Figure 4, we show that P_1 rises to P_2. In that case, the competitive firm will continue to produce Q_1 because the new marginal cost (MC_2) equals the new price (P_2) at a quantity of Q_1. In this case, the overcharge equals the difference between C_1 and C_2 times the quantity: $(C_2 - C_1)\,Q_1$. But there is no lost profit. The firm continues to earn a competitive return on its investment. In this case, the overcharge is grossly at odds with the damages sustained by the competitive firm because there were no damages at all.

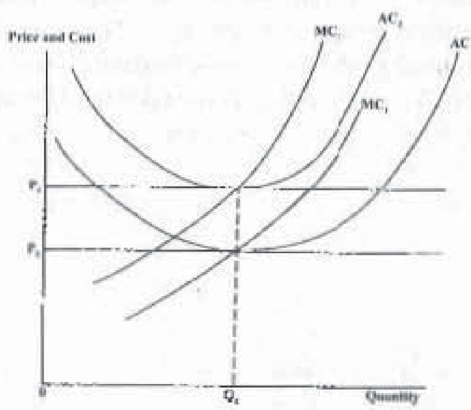

Figure 4

We have shown the polar cases. If industry demand is perfectly elastic (i.e., horizontal), the price does not rise, and lost profits clearly exceed the overcharge. If industry demand is perfectly inelastic (i.e., vertical), the price rises by the full amount of the overcharge, but profits are unaffected. In one case, the overcharge measure of damages is inadequate; while it is excessive in the

other. Now, demand is not apt to be perfectly elastic or perfectly inelastic, which means that the output price will rise but not by the full amount of the cost increase. In some cases, the price will rise enough for the overcharge to exceed the lost profits. In other cases, the price increase will be small enough for the overcharge to be less than the lost profit. The precise circumstances will dictate the final outcome because output demand elasticity and the shape of the firm's cost curves determine the relationship between the overcharge and lost profits. But the basic fact remains that the overcharge measure is an inexact proxy for the actual damages sustained, which are the lost profits.

395b. **Estimating the overcharge.** In spite of the (arguably) theoretical superiority of lost profits as a measure of damages in a price enhancement case, nearly all plaintiffs claim damages on the basis of an overcharge calculation. Since the actual prices paid are usually straightforward to establish,[11] the real problem arises in establishing the "but for" price.

395b1. *Before-and-after estimates.* Consider a before-and-after model applied to the price data presented in Table 1 and in Figure 5. The prices — suitably adjusted for inflation — of the proverbial widget were determined by competitive market forces from 2001 until 2011. It is well documented that a conspiracy began in 2012 and persisted through 2014. Just a glance at the data in either Table 1 or Figure 5 suggests that the substantially higher prices during 2012–2014 (the conspiracy period) were due to the conspiracy. Prior to the conspiracy, the average price was $51.82, in contrast to the prices of $80, $85, and $75 during the conspiracy period. But the question is not what the prices were in the past. Rather, the problem is estimating the prices for 2012–2014 had the conspiracy not occurred. The price data from the "before" period are (or at least may be) useful in estimating the "but for" prices during the "after" period.

11. It is not always true that the actual prices paid can be measured easily. The plaintiff cannot rely on list prices because list prices do not reflect the actual payments. The plaintiff must present evidence of actual transaction prices that reflect all discounts, rebates, and allowances, whether on the invoice or not. The relevant figures are the prices actually paid in the most literal sense.

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Table 1

Year	Price
2001	$50
2002	$45
2003	$50
2004	$60
2005	$55
2006	$40
2007	$50
2008	$45
2009	$60
2010	$55
2011	$60
2012	$80
2013	$85
2014	$75

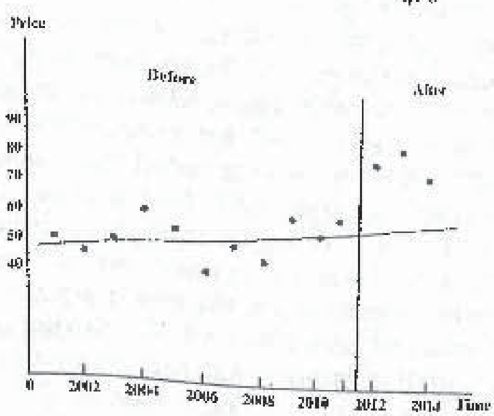

Figure 5

As a first approximation, one would look to see whether there was any trend in the price data. This can be done by fitting a regression line to the price observations prior to the conspiracy. The most basic model would be

$$P = \beta_0 + \beta_1 T$$

where P denotes price and T is time. Using the principles developed in ¶394, the data in Table 1 generate the following estimates:

$$\beta_0 = 47.18 \text{ and } \beta_1 = 0.77$$

The upward trend in the prices is captured by the estimate of β_1, which is positive and equal to 0.77. In other words, prior to the formation of the conspiracy, the price was drifting upward by $0.77 per year on average. In Figure 5, the regression line has been added to the price information. Based on the simple regression model, one would predict prices (rounded off) of $56 in 2002, $57 in 2003, and $58 in 2004. These "but for" prices would then be compared to the actual prices in order to estimate the overcharge per unit.

This simple model of damages presumes that whatever conditions were present during 2001–2011 continued to prevail during the conspiracy period. This is necessary in order to draw inferences regarding the 2012–2014 prices from the past prices. If something has changed in addition to the fact of collusion — this must be taken into account in estimating the "but for" prices during the conspiracy period. For example, there could have been substantial increases in some input costs. If the cost of producing our widget is sensitive to petroleum prices and there was an oil shock in 2002, one would expect widget prices to rise without the help of a price-fixing conspiracy. This increased cost must be taken into account. One way of doing this is to assume that the entire cost increase was passed on in the form of higher prices. In other words, to the estimated "but for" prices, one would simply add the increased cost of the petroleum products used in producing widgets. This adjustment is extremely conservative because cost increases are not usually passed on in their entirety.[12] A less conservative approach would be to examine the relationship between widget prices and petroleum prices in the pre-conspiracy period. This would require a more complicated regression model:

$$P = \beta_0 + \beta_1 T + \beta_2 O$$

where O denotes the oil price. Now, the predicted price of the widget will take into account all of the conditions captured by the passage of time plus the influence of oil prices.

There are other changes that could also account for some of the price increase. Similar cost increases have to be considered. For example, there may have been substantial increases in wages due to a new labor contract. Insurance costs may have risen because of a revised risk assessment. Regulatory changes may have imposed

12. See ¶396 for an examination of passing on overcharges.

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added costs. All of these influences should be considered in estimating the "but for" prices.

Widget prices are influenced by demand factors as well as cost considerations. Many of us may recall the dramatic increase in the demand for oat bran when it was first touted for its cholesterol-reducing properties. Grocery store shelves quickly emptied and prices rose. In the short run, changing productive capacity can be difficult. As a result, a sudden increase in demand will lead to price increases even in the absence of a conspiracy. To the extent that an increase in demand coincided with the formation of the widget cartel, the influence of the demand shift should be taken into account when estimating the but-for prices. For example, if there is a large change in population, then one would expect demand to shift and prices to rise. To account for this, one could add population to the regression model:

$$P = \beta_0 + \beta_1 T + \beta_2 O + \beta_3 POP,$$

where *POP* denotes population in the market. Now, the influence of any change in population that coincided with the price increase can be taken into account.

In effect, we have built a so-called reduced-form price equation. The widget price is expressed as a function of supply and demand variables. The selection of the variables should be guided by economic theory and the realities of the market in question. In many cases, the data will be limited, and therefore only the most important explanatory variables can be employed. Once the model is specified, the pre-conspiracy observations are used to estimate the coefficients in the regression equation: $\beta_0, \beta_1, \beta_2, \beta_3$. Then, the equation that we use for prediction is

$$P = b_0 + b_1 T + b_2 O + b_3 POP,$$

where b_0, b_1, b_2, and b_3 are the estimated coefficients of the model. In order to estimate the prices during the conspiracy period but for the cartel behavior, one substitutes the actual values of the explanatory variables (T, O, POP) for the conspiracy period in the estimated price equation. In this way, the plaintiff has controlled for changes in demand and supply determinants of price. The resulting prediction on price during the conspiracy period takes into account influences other than the conspiracy that could serve

to increase the widget prices. The differences between the predicted prices and the actual prices charged during the conspiracy period are inferred to be the overcharges due to the conspiracy.

An alternative formulation of the price equation is to add an indicator or dummy variable to the model. The equation would then be

$$P = \beta_0 + \beta_1 T + \beta_2 O + \beta_3 POP + \beta_4 D$$

where D is a binary variable that takes on the value 1 if the observation falls within the conspiracy period or 0 if the observation falls in the pre-conspiracy period. The coefficient on the dummy variable — that is, the estimate of β_4, is an estimate of the collusive overcharge — that is, the increase in price due solely to the anticompetitive behavior.

The data do not always cooperate in these econometric endeavors. As an example, consider the statistical results in the *Chicken Antitrust Litigation*.[13] The plaintiffs tried to use a price equation with a conspiracy dummy variable. In their price equation, they included the prices of beef, pork, and turkey, which are substitutes for chicken; seasonal dummy variables to control for time of the year; the consumer price index; consumer disposable income; per capita production of chicken to account for supply variation; and a dummy variable to isolate the effect of the conspiracy on price. Much to their surprise no doubt, the estimated coefficient on the collusion dummy variable was negative. This, of course, indicates that after taking other factors into account, the price of chicken during the conspiracy period was actually lower than it would have been absent the conspiracy. This, of course, is implausible because the point of a price-fixing conspiracy is to raise — not lower — price.[14] Assuming that there was, in fact, price-fixing behavior, the results suggest that a further refinement in the econometrics may be warranted. More sophisticated econometric methods may reveal the effects of conspiracy.

395b2. Some problems in practice. The before-and-after approach to estimating overcharge damages may run into some problems in practice. First, the before-and-after approach necessarily relies on time series data. In the widget hypothetical, annual

13. 560 F. Supp. 963 (N.D. Ga. 1980).

14. This is only true of colluding *sellers*; colluding buyers will take steps to reduce the prices that they pay. See ¶395e below.

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observations on price were available for the 2001–2011 period prior to the collusive behavior. Although one may be quite confident that there was no collusion during that period, some other things may well have changed. For example, the product itself is apt to change over time. All else being equal, product improvements may require higher prices because of higher costs. Moreover, product improvements that consumers presumably value will lead to shifts in the demand, which will also influence price. As the supply and demand conditions evolve over time, the plaintiff is forecasting outside the sample range. That is, the regression model estimates the relationship between supply and demand variables during one period while the forecast pertains to supply and demand variables that have not been incorporated in the estimation procedure. As a statistical matter, this tends to increase the standard errors of the estimates. In essence, the estimates are less precise.[15] One may argue that the observed price differential may be due to random error as well as the collusion, thereby casting doubt on the reliability of the damage estimates.

A second problem in practice involves identifying the beginning and ending of the conspiracy period. In some instances, there will be testimony regarding the advent of the conspiracy. In others, there may be a key event — a specific trade association meeting, for example — that provides a starting point. The plaintiff also needs to determine the end of the conspiracy if it wants to use post-conspiracy prices to estimate the "but for" prices during the damage period. It is obvious that a failure to identify precisely when the collusion occurred and when it did not will be critical to satisfactory damages estimation. A companion problem surfaces when the effect of the conspiracy lingers beyond the end of the formal collusion. This also taints the post-conspiracy prices and may give rise to extended damages.

Third, cartel activity may be subject to periodic episodes of cheating. If there is evidence that competition occurred from time to time during the conspiracy period, these prices may provide further evidence of "but for" prices. If there is no such evidence, then these competitive prices serve to confuse matters. In comparing the forecasted price with the actual prices, there will be instances where there is no measurable overcharge. In some cases, the difference may even be negative — that is, the predicted "but

15. *See* Franklin M. Fisher, *Multiple Regression in Legal Proceedings*, 80 Colum. L. Rev. 702 (1980).

for" price will exceed the actual price. These differences should not be netted out against the overcharges. Just because some of the prices were lower than anticipated is no reason to reduce the damages on those transactions where the prices were collusive.

Fourth, it may be true that one or more explanatory variables is influenced by the conspiracy. In an ideal cartel, all variables are specified: price, quantity, production quotas, nonprice variables (such as advertising, service, and warranty terms), credit terms, and so on. In practice, the cartel may not adequately control all of these variables. Suppose, for example, that the cartel members agree on price but do not allocate production quotas. As price is presumably higher than before the conspiracy began, each firm has an incentive to try to expand its output and thereby increase its market share. In effect, the colluders will compete on a nonprice basis.[16] To the extent that this inflates the expenditures on promotion, the "but for" estimate will be higher than it would have been otherwise. This, of course, will bias the damage estimate downward.

395b3. Yardstick estimates of overcharges. In some instances, the plaintiff may be able to use the yardstick approach to estimate overcharge damages. It is especially useful in cases where the pre-conspiracy prices are unreliable predictors of future prices — that is, in cases where the before-and-after approach is unavailing. As Hovenkamp has observed, "[t]he ideal conspiracy for the yardstick approach is a local cartel where a nearby market can be found which has the same basic cost structure."[17] It is also necessary that the yardstick market be as comparable as possible in all respects: degree of competition, tax structure, regulatory requirements, population density, average income, and so on. The selected yardstick will be vulnerable to attack if there are meaningful differences between the plaintiff's market and the yardstick market. It is possible to make some adjustments to account for the differences across the two markets. For example, suppose there is a difference in labor costs. One way of coping with this is to determine the labor cost per unit of output and adjust the "but for" price for the labor cost difference. Similar adjustments must be made for any other differences as well. If there is an important difference that is

16. In the limit, the expenditures on nonprice competition could completely dissipate the collusive profits. *See* George J. Stigler, *Price and Nonprice Competition*, 72 J. Pol. Econ. 149 (1968).

17. *See* Herbert Hovenkamp, Federal Antitrust Policy: The Law of Competition and Its Practice §17.5b (5th ed. 2015).

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beyond adjustment, this approach will have to be abandoned. Suppose, for example, that there are 3 competitors in the plaintiff's market and 20 in the yardstick market. There is a suspicion (at least) that, all else being equal, prices will be higher in a market with 3 participants relative to one with 20 competitors. There is, however, no a priori way to adjust for that difference. Consequently, one of these markets may not be a suitable yardstick for the other.

In some instances, an econometric approach to building a yardstick may be possible. The most prominent example involves bid-rigging claims. Since the bid riggers agree among themselves who is to win a particular job and no one submits a bid below that of the designated winner, this is a classic overcharge case. The measure of damage would be the difference between the rigged bid and the bid "but for" the collusion. Assuming that one knows which bids were rigged and which bids were competitively determined, it will be possible to apply a statistical yardstick. Using information on winning bids for sewer construction projects, Howard and Kaserman constructed two econometric models.[18] In the first model, the competitive winning bids were used to predict the "but for" bids on the jobs that were rigged. In the second model, they used all of the bids (rigged as well as competitive) but singled out the rigged bids by including a dummy variable.

Using the first approach, the competitive bids were assembled and all relevant characteristics were isolated. These characteristics included the number of bidders and the project size. In other circumstances, one might include other variables that would determine the bids in a competitive market. These bids, along with their associated characteristics, constituted the observations for a regression model of the following form:

$$B = \beta_0 + \beta_1 N + \beta_2 S + \varepsilon$$

where B is the bid, N is the number of bidders, S is the size of the project, and ε is the random error term.[19] The estimated coefficients, b_0, b_1, and b_2 were determined by the competitive bidding process. Thus, the plaintiff could use the estimated relationship,

18. *See* Jay H. Howard & David L. Kaserman, *Proof of Damages in Bid-Rigging Cases*, 34 Antitrust Bull. 359 (1989).

19. The size of the projects was determined by engineering cost estimates. *Id.* at 374.

$$B = b_0 + b_1 N + b_2 S$$

to predict the "but for" competitive bids that can be compared to the collusive bids.

The first regression equation estimated by Howard and Kaserman was[20]

$$B = 225{,}905 - 22{,}142N + 0.74S.$$

Thus, the data indicate that a competitive bid (on average) will be equal to $225,905 plus 74 percent of the engineering estimate of the cost, minus $22,142 times the number of bidders. The signs of the coefficients make sense and the R^2 was 0.847, which means that the model explained 84.7 percent of the variation in the competitive winning bids. The actual values for N and S associated with a specific *rigged* bid would be substituted into the equation to obtain an estimate of a competitive bid. The difference between that estimate and the actual winning bid is an estimate of the overcharge on that job. For example, if the engineering cost estimate were $500,000 and there were three bidders, then the econometric results would forecast a competitive "but for" bid of

$$B = \$225{,}905 - \$22{,}142\,(3) + 0.74\,(\$500{,}000) = \$529{,}479.$$

If the actual winning rigged bid had been, say, $750,000, a point estimate of the overcharge would be the difference between the actual bid (B_A) and the "but for" bid (B_{BF}):

$$B_A - B_{BF} = \$750{,}000 - 529{,}479 = \$220{,}521.$$

Two caveats are in order. First, this procedure will not work unless the plaintiff can identify which bids are competitive and which are collusive. Second, the statistical results will be weak if the number of competitive bids is small. The precision of the parameter estimates falls as the number of observations falls.

There is another econometric approach to estimating the overcharge on rigged bids: pool all of the bids together and use a dummy variable for the rigged bids. Howard and Kaserman specified their second regression model as

20. *Id.* at 390.

$$B = \beta_0 + \beta_1 N + \beta_2 S + \beta_3 R + \varepsilon$$

where R is a dummy variable that takes on the value of 1 for rigged bids and the value of 0 for competitive bids. Obviously, even with this approach the plaintiff must still be able to identify those bids that were rigged in order to use this variant. In this case, however, the coefficient on R provides an estimate of the average collusive overcharge on the rigged bids. Howard and Kaserman had a sample of 46 winning bids — 39 competitive bids and 7 rigged bids. In their second model, they used all 46 observations. Their results were as follows:

$$B = 65{,}178 - 52{,}550N + 1.02S + 586{,}834R.$$

The regression results were very good in a statistical sense. The regression coefficients were statistically significant and had the predicted signs; the R^2 was 0.914, which means that the model explained 91.4 percent of the observed variation in the winning bids. The coefficient on N indicates that the presence of an additional bidder reduced the winning bid by $52,550. The coefficient on size indicates that the winning bid rose by $1.02 for every dollar increase in the engineering estimate of the project size. Finally, the coefficient on R indicates that the winning rigged bid was $586,834 higher than the winning competitive bid. Thus, the coefficient on R is a measure of the average overcharge across all of the rigged bids after controlling for differences in project size and the number of bidders. When there is a single plaintiff, the total damage estimate can be computed by multiplying the average overcharge times the number of rigged bids. In such cases, it does not matter that the plaintiff has not identified the overcharge on a per-project basis. Because this formulation does not separate the overcharges on a per-project basis, however, it does not work when there are multiple plaintiffs. When there are several municipalities filing suit, for example, it would seem necessary to use the first regression model so that project-specific overcharges could be estimated.

395c. **Spurious damage estimates.** Some damage methodologies will produce spurious damage estimates. Suppose that the plaintiff compares prices in the post-conspiracy period with prices during the conspiracy period. If the price of a major input has increased between the conspiracy and post-conspiracy periods, the plaintiff must control for that cost increase. One way of doing this

is to construct a cost-adjusted
of the output price to input p
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The long-run cost curve i
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Since quantity was assumed

$$\frac{C_1/}{w_1}$$

21. We are indebted to David L. K
22. A good exposition is provided
A Mathematical Analysis 252–54 (2d ed.

is to construct a cost-adjusted price of the output equal to the ratio of the output price to input price. The cost-adjusted price is used as the dependent variable in a regression model estimated using observations in the post-conspiracy — presumably competitive — period. These regression results are used to predict "but for" prices during the conspiracy period. Any deviation between the observed cost-adjusted prices during the conspiracy period and the "but for" prices is then interpreted as an illegal overcharge.

If the input price that is used in constructing the cost-adjusted price is increasing over time, this approach will generate a positive damage estimate even if the defendants have charged competitive prices at all times.[21] This built-in bias toward a finding of overcharges when in fact there have not been any is due to the concavity of the long-run cost curve in input prices.[22] This can be seen quite easily. Let P_1 and P_2 represent the prices of the output in periods 1 and 2, respectively. Let w_1 and w_2 denote the prices of the input used as a cost proxy in periods 1 and 2, respectively. Finally, let C_1 and C_2 represent the total cost in periods 1 and 2, respectively. For simplicity, suppose that the firm's output is the same in both periods. If the price is at the competitive level in both periods, then $P_1 = C_1/Q$ and $P_2 = C_2/Q$ — that is, price will equal average cost in each period.

The long-run cost curve is concave in input prices. This means that the cost curve increases at a decreasing rate. This relationship is depicted in Figure 6. It is apparent that the slope of a straight line from the origin to the cost curve gets flatter as the input price (w) increases. But the slope of the straight line is C_1/w_1 and C_2/w_2, respectively. As a result,

$$\frac{C_1}{w_1} > \frac{C_2}{w_2}.$$

Since quantity was assumed to be constant, it will be true that

$$\frac{C_1/Q}{w_1} > \frac{C_2/Q}{w_2}.$$

21. We are indebted to David L. Kaserman for bringing this example to our attention.
22. A good exposition is provided by Eugene Silberberg, The Structure of Economics: A Mathematical Analysis 252–54 (2d ed. 1990).

Because price is equal to average cost in each period, it follows that

$$\frac{P_1}{w_1} > \frac{P_2}{w_2}.$$

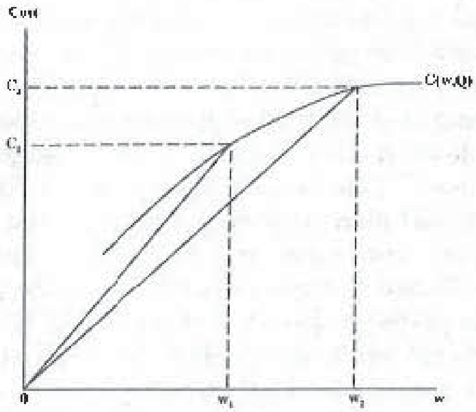

Figure 6

Using the cost-adjusted price in period 2 as a competitive benchmark, the plaintiff will estimate positive damages even though there are no damages at all. This spurious result will be exacerbated if the quantity sold in period 2 increases due to, say, growth in the market.

A simple numerical example. Suppose that the output is produced with inputs in fixed proportions. Each unit of output (Q) requires exactly one unit of each input.[23] For example, a hammer requires one handle and one hammerhead. Suppose that in the alleged conspiracy period, the price of input 1 (w_1^1) is $1.00 and that the price of input 2 (w_2^1) is also $1.00. Because each unit of output requires one unit of each input, the average (and marginal) cost of production will be $2.00. In period 2, suppose that the price of input 1 (w_1^2) increases to $2.00, but that the price of input 2 (w_2^2) does not change. Thus, average cost in period 2 will be equal to $3.00.

23. This production function is written as

$$Q = \min\{X_1, X_2\}$$

where X_1 and X_2 are the quantities of inputs 1 and 2. For example, if we had 10 handles and 14 hammerheads, output would be the minimum of the two input quantities: $Q = 10$.

In period 2, the post-co
competitive level, which is
$3.00. If we look at the so-c

$$\frac{P^2}{w_1^2}$$

Suppose that the price i
level — that is, P^1 = $2.00. T

$$\frac{P^1}{w_1^1}$$

Note that the firm charged a
therefore there is clearly nc
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could be overcharges in period 1 that

In period 2, the post-conspiracy period, output price is at the competitive level, which is equal to average cost — that is, $P^2 = \$3.00$. If we look at the so-called cost-adjusted price, we observe

$$\frac{P^2}{w_1^2} = \frac{\$3.00}{\$2.00} = 1.5.$$

Suppose that the price in period 1 was at the competitive level — that is, $P^1 = \$2.00$. Then the cost-adjusted price will be

$$\frac{P^1}{w_1^1} = \frac{\$2.00}{\$1.00} = 2.0.$$

Note that the firm charged a competitive price in both periods and therefore there is clearly no overcharge. But a comparison of the so-called cost-adjusted prices suggests that there was an overcharge:

$$\frac{P^1}{w_1^1} > \frac{P2}{w_1^2}.$$

This approach obviously generates purely spurious damage estimates. Irrespective of the competitiveness of the output prices,[24] this approach is guaranteed to produce positive damages as long as the input price that is used as a proxy for average cost increases in the post-conspiracy period. If the plaintiff is going to use this method, all of the costs must be used for the adjustment. In our simple example, one should compare P^1/AC^1 and P^2/AC^2:

$$\frac{P^1}{AC^1} = \frac{\$2.00}{\$2.00} = \frac{P^2}{AC^2} = \frac{\$3.00}{\$3.00}.$$

This avoids the problem of spurious inferences.

In some cases, the plaintiff will have price data before, after, and during the conspiracy. All of the data provide useful information for purposes of damage estimation, and therefore all of the

24. If the price of the input used as a proxy falls in the post-conspiracy period, there could be overcharges in period 1 that will go undetected.

data should be employed in the damage estimation.[25] Consider the price data plotted in Figure 7. There are 10 pre-conspiracy observations, 10 post-conspiracy prices, and 7 prices during the conspiracy period. It is fairly clear that the price data exhibit a general downward drift. Before, during, and after the alleged damage period, there appears to be a negative trend. This trend could be due to a continuing improvement in the production process that leads to declining costs. If the plaintiff estimates a reduced-form price equation over the post-conspiracy period and applies it to the conspiracy period, spurious damages may be estimated. It is difficult to model the gradual improvement in the production technology. As a result, the reduced-form price equation is apt to miss this influence. When the regression equation is applied to the damage period, it will generate positive damage estimates even if there are none because of the higher costs of production. This is an instance where the plaintiff should use all of the prices in the regression model and include a dummy variable for the conspiracy period. In this way, all of the available information will be used, and the effects of the conspiracy — if any — will be isolated in the coefficient on the dummy variable.

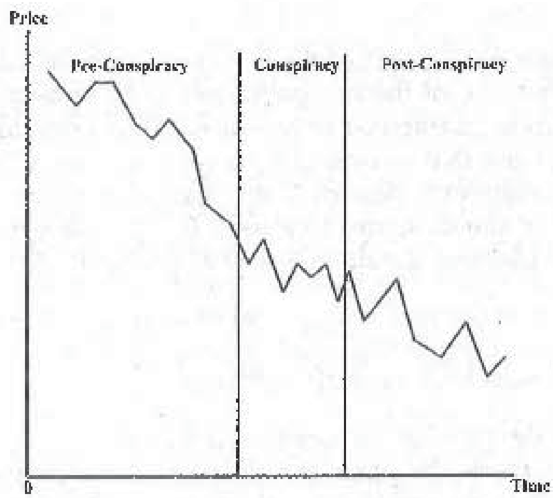

Figure 7

25. As an econometric matter, the added observations will improve the precision of the estimates — that is, the standard errors of the estimates will be smaller with more observations.

395d. Overcharges
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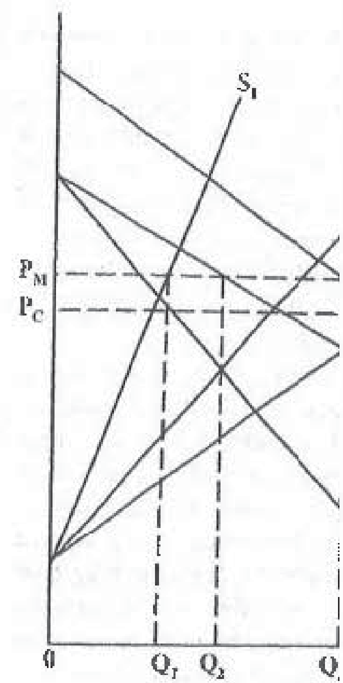

26. In this section, we employ
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Econ. Rev. 139 (1970), and William
trust Cases, 94 Harv. L. Rev. 937 (198
27. Partial conspiracies are an
trust Economics 146–51 (2d ed. 2009
28. The following analysis has
is alleged. Roger D. Blair & Richard
pants in a Price-Fixing Conspiracy: Lia

395d. Overcharges and partial conspiracies.[26] A complication arises when a price-fixing conspiracy does not involve the entire industry.[27] In an oligopoly, one firm could simply refuse to participate.[28] In an industry with a handful of large firms and a significant number of small firms, the dominant firms may decide to collude but not bother to include the smaller fringe firms. In this setting, the economic analysis is uncontroversial. Consider Figure 8, in which demand is represented by D and industry supply is $S_1 + S_2$. Absent collusion, the competitive price will be P_C and the

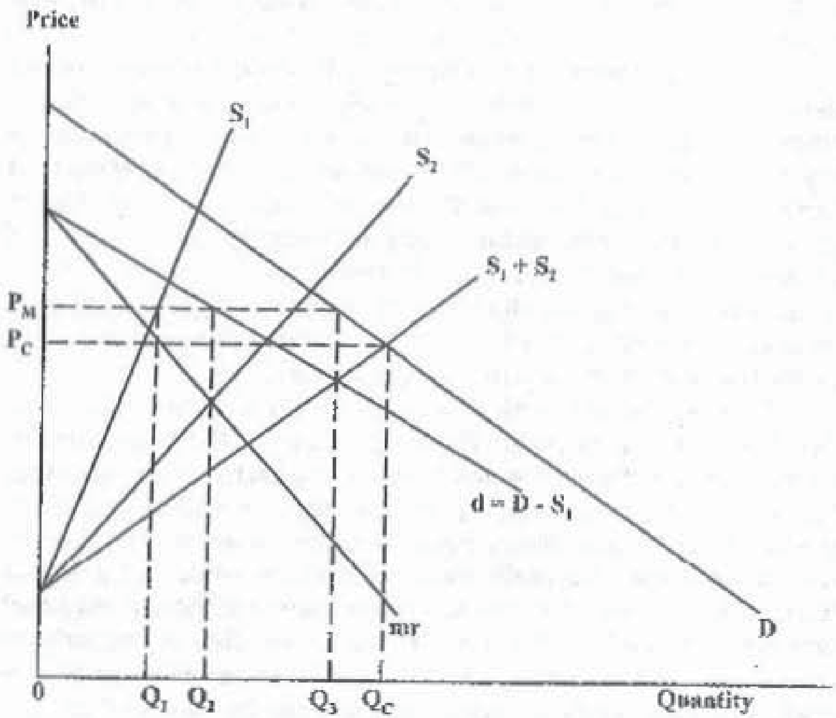

Figure 8

26. In this section, we employ the dominant firm model, which has been used to good advantage by Thomas R. Saving, *Concentration Ratios and the Degree of Monopoly*, 11 Int'l Econ. Rev. 139 (1970), and William M. Landes & Richard A. Posner, *Market Power in Antitrust Cases*, 94 Harv. L. Rev. 937 (1981).

27. Partial conspiracies are analyzed in Roger D. Blair & David L. Kaserman, Antitrust Economics 146–51 (2d ed. 2009).

28. The following analysis has been used to identify nonparticipants when collusion is alleged. Roger D. Blair & Richard E. Romano, *Distinguishing Participants From Nonparticipants in a Price-Fixing Conspiracy: Liability and Damages*, 28 Am. Bus. L.J. 33 (1990).

corresponding quantity will be Q_C. Suppose we disaggregate industry supply into two components: S_1 is the supply of the noncolluders and S_2 is the supply of the colluders. The colluders will maximize their profits by taking into account the supply response of the noncolluders in their calculations. In effect, the colluders concede part of the market to the noncolluders. In Figure 8, this concession is reflected in the residual demand curve, which is the difference between the market demand (D) and the supply response of the noncolluders (S_1). Thus, the residual demand, labeled $d = D - S_1$, shows the quantity available for sale by the colluders after taking into account the supply responses of the noncolluders.

In order to maximize collusive profits, the cartel will produce the quantity where the cartel supply (S_2) equals the marginal revenue associated with the residual demand (mr). The optimal quantity for the colluders, which is shown as Q_2 in Figure 8, yields a cartel price of P_M. The noncolluders will respond to the higher price in the market by sliding along their supply curve (S_1) to the price in the market. In this example, the noncolluders will produce Q_1 at a price of P_M. Together, the cartel output (Q_2) and the noncolluders' output (Q_1) will equal Q_3, which is the quantity that clears the market at the collusive price of P_M.

Consider the economic results of this conspiracy. The price in the market has risen from P_C to P_M. That is, the overcharge is clearly equal to the difference between P_M and P_C. It is also true that all buyers pay the same price, and therefore all buyers suffer the same overcharge. Every buyer faces the same problem: proving the price that it actually paid, proving the price that it would have paid "but for" the conspiracy, and proving the quantity that was actually purchased. It does not matter whether the buyer purchased from a colluder or a noncolluder — the overcharge is precisely the same. The problem of establishing the "but for" price is no more severe for purchasers from the conspirators. The damages cannot be characterized as speculative because purchases were not made from the actual colluders. If the damage claims are speculative, it is because the "but for" price was not proven with the appropriate degree of precision.

395d1. *Duplicative recovery.* The next question is who should compensate the purchasers of the noncolluders. The obvious answer is that the cartel members should bear the full costs of their illegal behavior. This, of course, would include the overcharges

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product differentiation.

imposed on all buyers of the product in question.[29] This may raise concerns about duplicative recovery. Such concerns seem misplaced. First, the recoveries would not be duplicative in the sense that a single overcharge was being recovered by more than one antitrust victim. For example, in Figure 8, let P_M be \$10, P_C be \$8, and Q_3 be 300. The total overcharge will be $(P_M - P_C)\ Q_M = (\$10 - 8)(300)$, which is \$600. Permitting the customers of the noncolluders to recover from the cartel members would not increase the total overcharge. Suppose that Q_1 equals 125 and Q_2 equals 175. It is true that the overcharge collected by the cartel members is $(\$10 - 8)(175)$ or \$350. The customers of the noncolluders have been overcharged $(\$10 - 8)(125)$ or \$250, but the conspirators did not collect that portion of the total overcharge. This does not make their recovery duplicative. It simply does not duplicate any part of the overcharge recovery accorded to the customers of the conspirators. It is true, of course, that the cartel members will have to repay more than they collected in overcharges, but it cannot be denied that they are responsible for the total overcharges suffered by all buyers.

395d2. Product differentiation. The logic of the umbrella model is most compelling when the product is homogeneous. Product differentiation introduces some difficulties because the overcharge is not the same across all producers.[30] Product differentiation may lead to equilibrium price differentials across the various brands. A conspiracy among a subset of all producers will upset these differentials, and market forces will lead to price adjustments by the nonconspirators. Again, the overcharge will be the difference between the new price and the "but for" price. If the "but for" price cannot be estimated without speculation, the umbrella plaintiffs will be out of luck.

It may be appropriate, if data are available, to include observations of nonconspirators in the estimation of the overcharge. First, this requires being able to distinguish between firms that participated in a price-fixing cartel and firms that did not participate. If product differentiation or other reasons lead the identified nonconspirator firms to behave contrary to the umbrella pricing

29. For a more extensive analysis, see Roger D. Blair & Christine A. Piette, *Umbrella Pricing*, *in* Issues in Competition Law and Policy (Wayne D. Collins ed., 2007).

30. Herbert Hovenkamp, Federal Antitrust Policy: The Law of Competition and Its Practice §16.6 (5th ed. 2015), makes this point. *See* R.D. Blair & R.E. Romano, *supra*, 28 Am. Bus. L.J. at 33, for a technical demonstration that the logic carries through in the presence of product differentiation.

model, then an expert may include those nonconspirator observations in the econometric model, and code them as not part of the conspiracy in all periods considered: before, during, and after the conspiracy.

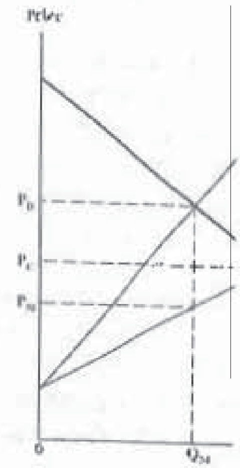
Consider a coffee cartel. There are many varieties of coffee: Colombian, Kona, Jamaican Blue Mountain, and so on. Even though there is product differentiation, the cartel can (in principle at least) agree on a new price structure. This case may pose some additional difficulties, but they should not be insurmountable. More troublesome, however, are consumers of tea, hot chocolate, milk, fruit juices, and other imperfect substitutes for coffee. As an economic matter, one would expect a collusive increase in the price of coffee to cause changes in the prices of these imperfect substitutes. Proving the extent of the price change in these products that can be attributed to the increased coffee price is apt to be quite difficult in practice. In principle, these antitrust victims should be afforded an opportunity to prove their damages, but they are apt to be denied standing.

395e. Collusive monopsony and damages. When buyers collude, their aim is to reduce the quantity purchased and depress the price below the free market level. This is price-fixing behavior that imposes welfare losses that are analogous to those imposed by traditional cartels. Collusive monopsony is a per se violation of the Sherman Act[31] and invokes §4 of the Clayton Act. The principles of damage estimation can be used to estimate *undercharges* in the collusive monopsony cases.

395e1. Collusive monopsony.[32] The effects of collusive monopsony can be seen with the aid of Figure 9. The collective demand of the buyers is shown as *D* and the supply is shown as *S*. If the buyers compete with one another in the market, they will expand their purchases to the point where supply and demand are equal. As a result, the competitive price will be P_C and the competitively determined quantity will be Q_C. Following the formation of a buying cartel, the firms collectively recognize their buying power, which flows from the positive slope of the supply curve. They will understand that the price can be depressed if they agree

31. *Mandeville Island Farms v. American Crystal Sugar Co.*, 334 U.S. 835 (1947). See ¶2011 for a discussion. *Also see* Roger D. Blair & Jeffrey L. Harrison, *Antitrust Policy and Monopsony*, 76 Cornell L. Rev. 297 (1991); Roger D. Blair & Jeffrey L. Harrison, *Cooperative Buying, Monopsony Power, and Antitrust Policy*, 86 Nw. U. L. Rev. 331 (1991).

32. A more complete exposition of the theory of monopsony and its collusive variant is contained in Roger D. Blair & Jeffrey L. Harrison, Monopsony in Law and Economics 36–61 (2010).



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$$\Delta = (P_C$$

33. Total expenditures will be $TE = P($ on *TE* is $dTE/dQ = P + QdP/dQ$. This is the ply curve because dP/dQ is positive.

34. *See* Joan Robinson, The Economic brief discussion of monopsonistic exploitat

35. In Figure 9, it is clear that collusior unsold units involve losses but will be uncom priced out of a market by a cartel of sellers ca

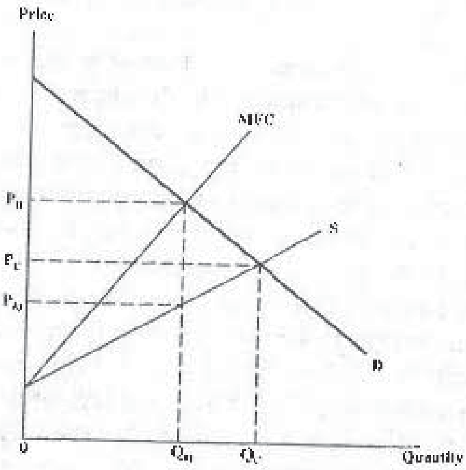

Figure 9

to buy less. This effect is reflected in the marginal factor cost (MFC), which is the increase in total expenditures when the quantity purchased increases by a small amount.[33] Profit maximization by the colluders requires restricting purchases to the point where demand equals marginal factor cost. In Figure 9, we see that this occurs at a quantity of Q_M. The price on the supply curve that corresponds to Q_M is P_M. For the quantity Q_M, the price on the demand curve is P_D. The buying cartel, therefore, imposes an undercharge of $P_D - P_M$ per unit in the sense that the marginal value of the good is P_D, but the price paid is only P_M. This is a measure of monopsonistic exploitation.[34] The damage, however, is the difference between the actual price paid (P_M) and the price "but for" the conspiracy, which would be P_C, times the quantity actually purchased (Q_M):[35]

$$\Delta = (P_C - P_M)\,Q_M.$$

33. Total expenditures will be $TE = PQ$. As Q increases by a small amount, the effect on TE is $dTE/dQ = P + QdP/dQ$. This is the marginal factor cost, which lies above the supply curve because dP/dQ is positive.

34. *See* Joan Robinson, The Economics of Imperfect Competition 281–83 (1933), for a brief discussion of monopsonistic exploitation.

35. In Figure 9, it is clear that collusion leads to a reduction in sales of $Q_C - Q_M$. These unsold units involve losses but will be uncompensated for the same reason that those who are priced out of a market by a cartel of sellers cannot recover for their losses: problems of proof.

The problem, of course, is how to measure this collusive undercharge.

395e2. *Measuring the damages.* Precisely the same empirical methods can be used for estimating undercharges as were used for estimating overcharges. All of the same problems arise in using the before-and-after approach: identifying the precise dates of the conspiracy and controlling for changes in supply and demand factors that would affect the "but for" price. Trying to use the yardstick model requires finding another market that is as similar to the plaintiffs' market as possible, which may be exceedingly difficult.

395f. **Overcharges in tying cases.** A tying contract involves a conditional sale: the seller will sell good *A* on the condition that the buyer also purchases good *B*.[36] In such arrangements, the tying good is *A* and the tied good is *B*. Usually, the customer plaintiff alleges that it was overcharged on the tied good and therefore is entitled to recover the difference between the competitive price of the tied good and the price that it actually paid.[37] This measure of damages, however, is not correct. The plaintiff is entitled to recover only the difference between the firm's actual condition and its condition "but for" the tying contract. This means that the plaintiff is not entitled to reformulate only part of the contract. Instead, the plaintiff must determine the net effect of reformulating the entire contract. This will be a daunting task and perhaps not worth the effort.

Consider the tying contract in *Siegel*.[38] The franchisor charged neither a franchise fee nor a running royalty (as most franchisors do), but it required that its franchisees purchase a certain number of cookers and fryers as well as packaging supplies and mixes exclusively from Chicken Delight. The prices for these tied products were higher than the prices of comparable products sold by other suppliers of the tied goods. The franchisee's damage, however, is not equal to the "overcharge" on these tied products because it got a license granting it the right to assume Chicken Delight's identity, to adopt its business methods, and to prepare and market chicken under the Chicken Delight trademark without a separate charge. The license must have been worth something or

36. On tying, see Chapter 17. For a more compact examination, see Herbert Hovenkamp, Federal Antitrust Policy: The Law of Competition and Its Practice §§10.1–10.3 (5th ed. 2015).

37. In addition to the buyers, sellers of the tied good may complain that they have been foreclosed from the market or at least a part of it. These claims will be examined in ¶397.

38. *Siegel v. Chicken Delight*, 448 F.2d 43 (9th Cir. 1971), *cert. denied*, 405 U.S. 955 (1972).

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39. *Kypta v. McDonald's Corp.*, 671 F.2
(1982).

the franchisees would not have agreed to the contract. The court recognized this and required the plaintiff to deduct a reasonable franchise fee from the sum of the overcharges on the tied items in measuring the damages. The result of this requirement is that the franchisee's damage equals the difference between the price paid for the tied package and the sum of the market prices of the tied and tying products. This requirement is articulated quite clearly in *Kypta*:

> . . . injury resulting from a tie-in must be shown by establishing that payments for both the tied and tying products exceeded their combined fair market value. The rationale behind this requirement is apparent: a determination of the value of the tied products alone would not indicate whether the plaintiff indeed suffered any net economic harm, since a lower price might conceivably have been exacted by the franchisor for the tying product. Unless the fair market value of both the tied and tying products are determined and an overcharge in the complete price found, no injury can be claimed; suit, then, would be foreclosed.[39]

Usually, it will not be possible for a franchisee to prove any injury under this formula.

Suppose that over the life of Siegel's franchise he paid a premium for the cookers and fryers that he bought from Chicken Delight when he became a franchisee. In addition, suppose he paid a premium for the packaging materials and mixes that he needed to operate his fast-food restaurant. For illustrative purposes, suppose that the overcharge on the equipment plus the present value of the overcharges on the packaging supplies and mixes over the life of the franchise amounted to $250,000. The fair market value of the franchise license must have been worth at least $250,000 to Siegel or he would not have become a Chicken Delight franchisee. As a result, Siegel has suffered no injury at all. Of course, he would like to reformulate the contract in part. He would like to be a Chicken Delight franchisee with a zero franchise fee and no running royalty, and be able to buy equipment and supplies at competitive market prices. But if the contract were to be reformulated, Siegel might have to pay a franchise fee of $250,000. Alternatively, he might pay a combination of a franchise fee and a running royalty. The net result is that he will be better off (if at all) by less than

39. *Kypta v. McDonald's Corp.*, 671 F.2d 1282, 1285 (11th Cir.), *cert. denied*, 459 U.S. 857 (1982).

the $250,000 that he is no longer "overcharged" on the equipment and supplies.

More generally, any time that there is an overcharge on the tied good, there must be an undercharge on the tying good. At a minimum, this creates a serious problem in estimating damages. In addition to estimating the overcharge on the tied goods, the plaintiff must estimate the discount on the tying good. In many cases, the plaintiff can readily measure the overcharge on the tied good(s) simply by comparing the actual price(s) paid to market price(s) on comparable products. Of course, it will be necessary to establish that the tied products are actually comparable to the products available from rivals. But the real problem is estimating the price of the tying good absent the tying contract. If the defendant possesses real market power in the tying good, there will be no close substitutes for comparison purposes.

395g. Overcharges in merger cases. Horizontal mergers — that is, mergers between competitors — may cause a change in industry structure that is competitively significant. All horizontal mergers necessarily reduce the number of competitors. If the premerger industry structure is sufficiently unconcentrated, a merger may have no competitive significance.[40] Indeed, in such a setting, the merger is apt to be motivated by efficiencies and therefore would tend to be procompetitive and certainly no worse than competitively neutral. In other instances, however, the post-merger market structure may become sufficiently noncompetitive that price will rise following the merger. In those cases, there may be illegal overcharges that require estimation.

Suppose two firms merge and the post-merger price exceeds the pre-merger price. If the merger violates §7 of the Clayton Act, customers may sue for damages. In this case, the overcharge will be equal to the difference between the actual post-merger price and the price that would have prevailed but for the merger. The usual estimation problems surface: conducting a satisfactory before-and-after analysis or finding a suitable yardstick market. All of the remarks that were made above apply with equal force to damages in horizontal merger cases. Moreover, the analysis of partial conspiracies also applies here. If, say, two of the ten market participants merge and industry price rises as a consequence, all buyers

40. While the merger may have little competitive effect, there would be small changes in price and output resulting from the merger. These changes may be extremely difficult to detect through statistical analysis.

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44. Damages for terminate
45. For a detailed examin
Herndon, & John E. Lopatka, *R*
Wash. U. L.Q. 657 (2005).

experience the overcharge and therefore all have suffered antitrust injury and damages. All buyers should be able to sue, and the newly merged entity would seem to be the culprit. Since no other supplier was involved in an antitrust violation, these firms cannot be held *responsible* for the overcharge even though they collected a part of it. The merging firms, however, are responsible for all of the overcharge because "but for" the merger there would not have been an overcharge.

395h. **Resale price maintenance and antitrust damages.** Resale price maintenance (RPM) is a vertical price restraint. A seller conditions the sale of its product on an agreement not to resell the product at a price below some specific level.[41] As a contract in restraint of trade, RPM had been illegal per se since *Dr. Miles*.[42] But in 2007, the Supreme Court overturned *Dr. Miles* in its *Leegin*[43] decision. Now, RPM is subject to the rule of reason and, therefore, the economic consequences have to be analyzed. Most of the private cases are filed by terminated dealers who refused to acquiesce to the price restraint.[44] In principle, however, customers who cannot buy from discounters may claim that they have suffered overcharges. The measure of damages would be equal to the difference between the price actually paid and the price that would have prevailed absent the illegal RPM agreement. Such a claim poses conceptual problems as well as problems of estimation.[45]

395h1. Conceptual problems. It is not entirely clear that consumers of products subject to RPM have been injured at all. If in fact the RPM was motivated by either a dealer cartel or a manufacturer cartel, then per se illegality follows and consumers are clearly overcharged. In cases involving a dealer cartel, there is no conceptual problem because the overcharges are clearly illegal. Consumers have suffered antitrust injury and antitrust damages. In cases involving a manufacturer cartel, the dealers are the direct purchasers who have been overcharged and presumably will sue for damages. Again, there is no conceptual problem: the overcharge is like any other resulting from a price-fixing cartel.

41. For the substantive law, see Subchapter 16B-1.
42. *Dr. Miles Med. Co. v. John D. Park & Sons Co.*, 220 U.S. 373 (1911).
43. *Leegin Creative Leather Prods., Inc. v. PSKS, Inc.*, 551 U.S. 877 (2007).
44. Damages for terminated dealers are examined in ¶397.
45. For a detailed examination of the problems that arise, see Roger D. Blair, Jill B. Herndon, & John E. Lopatka, *Resale Price Maintenance and the Private Antitrust Plaintiff*, 83 Wash. U. L.Q. 657 (2005).

A substantial literature on RPM has developed, however, that does not involve cartel activity. This literature offers efficiency justification for RPM, which undermines anticompetitive concerns.[46] In essence, the manufacturer wants its distributors to provide product-specific services that lead to a shift in the demand curve for the product.[47] If the demand shift is parallel, this means that the value of the product with the product-specific services is higher than the value of the product without the services. As a simple example, consider Figure 10. Demand curve D_1 represents the value to consumers of a product without the services. When the distributor provides product-specific services, the value of the product rises and demand shifts to D_2. As an example, it is easy to see that a cell phone that has many bells and whistles and includes thorough instructions on how to use the phone is worth more to the consumer with than without the instructions. On the supply side, the provision of product-specific services is not free. Accordingly, the supply of the product with the services (S_2) lies above the

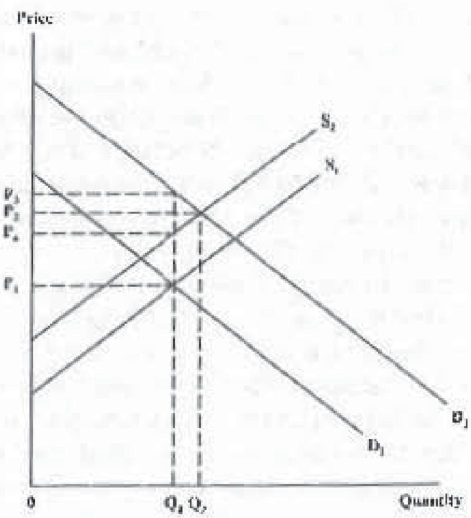

Figure 10

46. The result has been substantial controversy. For a review of the conflicting views, see Chapter 11 in Herbert Hovenkamp, Federal Antitrust Policy: The Law of Competition and Its Practice (5th ed. 2015).

47. *See* Lester Telser, *Why Should Manufacturers Want Fair Trade?*, 3 J.L. & Econ. 86 (1960).

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result, under *Illinois Brick*,[48] they w

48. *Illinois Brick v. Illinois*, 431 U.S. 720 (197
law to indirect purchasers. See ¶¶346, 396.

supply without the services. Notice that the provision of product-specific services not only leads to an increase in price from P_1 to P_2, but quantity also increases from Q_1 to Q_2. The reason for this outcome is that the demand curve shifted more than the supply curve. This can be seen at Q_1. The value of Q_1 with the services is P_3 whereas the cost of Q_1 with the services is P_4.

In these circumstances, RPM is used to prevent free riding. Because the product-specific services can often be consumed without buying the product, there is an incentive for discounters to skimp on services. The consumers will get the benefits of the full-service distributors but will be lured to the discounters by their lower prices. In effect, the discounters free-ride on the efforts of the full-service distributors. Now, the manufacturers are concerned about free riding because it undermines the incentives of the full-service distributors. As formerly full-service distributors begin to reduce their services, the demand curve will shift back to D_1. This results in fewer sales and lower profits for the manufacturer. By imposing RPM, the manufacturer can blunt the consumer's incentive to shop around for a lower price. There will be no reward for consuming product-specific services at one location while buying the product at a separate location.

It is true that RPM prevents discounting, and therefore the prices paid by some consumers will be higher than they would be if discounting were permitted. But the consequences of discounting may be the elimination of product-specific services and consequent reduction in the value of the product. Clearly, the marginal consumer at a quantity of Q_1 is no worse off paying P_2 and getting services along with the product than he or she would be paying P_1 but not getting the service. Consequently, the consumer arguably has not been injured.

395h2. *Estimation problems.* In cases where cartel activity of the dealers or of the manufacturers explains the existence of RPM, the overcharges are the same as in any price-fixing case. If the distributors are fixing prices, the consumers are overcharged directly. As a consequence, they would have standing, and damage estimation would proceed as described above. If the manufacturers are engaging in cartel activity, RPM is used as a means of preventing cheating. Consumers in that case are overcharged indirectly. As a result, under *Illinois Brick*,[48] they will not have antitrust standing.

48. *Illinois Brick v. Illinois*, 431 U.S. 720 (1977), denies damage recoveries under federal law to indirect purchasers. See ¶¶346, 396.

The distributors would be the direct purchasers and therefore would have standing. Again, there is nothing special about their damage estimation problem.

Things are far more confused in the case of RPM that is motivated by a desire for product-specific services coupled with free riding. As a conceptual matter, it is not clear that there is an overcharge in the usual sense of the term. One possible measure of the "overcharge" would be the difference between the actual price paid and the price that a discounter would charge. If there are no discounters, it will be very difficult to estimate the "but for" price because there will be no evidence. If there are discounters, the discounted prices provide a benchmark, but the plaintiff would seem to have failed to mitigate if he or she did not buy from the discounter. If the discounted prices were only available for a short period, those prices provide a benchmark, but the manufacturer would seem to be entitled to an offset for the value of the product-specific services that RPM made possible.

¶396. Damages for Indirect Purchasers

In a pair of decisions — *Hanover Shoe*[1] and *Illinois Brick*[2] — the Supreme Court made it clear that only *direct* purchasers have standing to sue for overcharge damages under §4 of the Clayton Act. In an earlier case against United Shoe Machinery, the government challenged United Shoe Machinery's business practice of leasing, but not selling, its machines.[3] The trial court found this practice to be a monopolizing device.[4] Hanover Shoe had been one of United Shoe Machinery's lessees and following the government's victory filed suit for damages, claiming to have been overcharged.[5] United Shoe Machinery objected that Hanover Shoe had not actually suffered any damages because it had passed on any overcharge to its customers in the form of higher shoe prices. The

¶396. n.1. *Hanover Shoe v. United Shoe Mach. Corp.*, 392 U.S. 481 (1968).

2. *Illinois Brick v. Illinois*, 431 U.S. 720 (1977).

3. *United States v. United Shoe Mach. Corp.*, 110 F. Supp. 295 (D. Mass. 1953), *aff'd*, 347 U.S. 521 (1954).

4. This decision has created some controversy. See ¶614; John S. Wiley Jr., Eric Rasmussen, & Mark Ramseyer, *The Leasing Monopolist*, 37 UCLA L. Rev. 693 (1990); Scott E. Masten & Edward A. Snyder, *United States versus United Shoe Machinery: On the Merits*, 36 J.L. & Econ. 33 (1993). For a contrary view, see Joseph F. Brodley & Ching-To Ma, *Contract Penalties, Monopolizing Strategies, and Antitrust Policy*, 45 Stan. L. Rev. 1161 (1993).

5. It is doubtful that such damages actually existed. See Roger D. Blair & Jill B. Herndon, *A Note on* Hanover Shoe, 43 Antitrust Bull. 365 (1998).

Supreme Court rejected this
concerns. First, the Court w
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already were.[6] In addition, th
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396a. Complexity of
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6. *Hanover Shoe*, 392 U.S. at 493.
situations, see George Kosicki & Miles
Purchases Antitrust Cases, 51 Antitrust B

7. *Hanover Shoe*, 392 U.S. at 493–9

8. *Illinois Brick*, 431 U.S. at 736.

9. See ¶346; William M. Landes &
Standing to Sue Under the Antitrust Laws
Rev. 602 (1979); Robert Harris & Lawre
Comprehensive Policy Analysis, 128 U. Pa.
Posner, *The Economics of Passing On: A*
(1980); Robert Cooter, *Passing On the M*
Theory, 129 U. Pa. L. Rev. 1523 (1981).

Supreme Court rejected this pass-on defense and expressed two concerns. First, the Court was concerned that a pass-on defense would make antitrust cases far more complicated than they already were.[6] In addition, the Court was concerned that a pass-on defense could so diffuse the overcharges that some antitrust violations would go unchallenged.[7] As a result, the Court would not permit the defensive use of the pass-on theory.

In *Illinois Brick*, the Supreme Court confronted a symmetric problem. The State of Illinois had purchased buildings from contractors who had purchased masonry services from subcontractors. These subcontractors had purchased cement blocks from manufacturers who had been accused of fixing prices. Illinois, in effect, was an indirect purchaser of cement block and wanted to recover the overcharges that it had incurred as a result of the conspiracy. The Supreme Court recognized that it would have to overrule *Hanover Shoe* if it were going to permit indirect purchasers to recover.[8] For a variety of reasons, it was unwilling to do this. Damage calculations would be complex, resources used in litigation would dissipate the damage award, and the incentives for private enforcement would be weakened. As a result, the Court limited recovery to direct purchasers. Thus, the offensive use of the pass-on theory is not permitted.

396a. Complexity of damage calculations for indirect purchasers. The Court expressed considerable concern about the complexity of antitrust suits if indirect purchasers had standing to sue. In the aftermath of *Illinois Brick*, there was vigorous debate regarding the Court's concern.[9] Under some circumstances, the economics is quite clear in principle, but there are practical problems of measurement that cannot be denied or ignored. These practical problems of proof can undermine private suits and thereby weaken the deterrent effect of §4 of the Clayton Act. The following examples will illustrate the difficulties.

6. *Hanover Shoe*, 392 U.S. at 493. On the complexity of damages estimation in such situations, see George Kosicki & Miles B. Cahill, *Economics of Cost Pass Through in Indirect Purchases Antitrust Cases*, 51 Antitrust Bull. 599 (2006).

7. *Hanover Shoe*, 392 U.S. at 493–94.

8. *Illinois Brick*, 431 U.S. at 736.

9. See ¶346; William M. Landes & Richard A. Posner, *Should Indirect Purchasers Have Standing to Sue Under the Antitrust Laws? An Economic Analysis of* Illinois Brick, 46 U. Chi. L. Rev. 602 (1979); Robert Harris & Lawrence Sullivan, *Passing On the Monopoly Overcharge: A Comprehensive Policy Analysis*, 128 U. Pa. L. Rev. 269 (1979); William M. Landes & Richard A. Posner, *The Economics of Passing On: A Reply to Harris and Sullivan*, 128 U. Pa. L. Rev. 1274 (1980); Robert Cooter, *Passing On the Monopoly Overcharge: A Further Comment on Economic Theory*, 129 U. Pa. L. Rev. 1523 (1981).

396a1. *Fixed proportions.* Suppose that the manufacturers of television sets conspire to raise the price that they charge to their distributors. The distributors compete with one another for resales of television sets to consumers. This three-tier system is as simple as it can get. Since there must be one television set purchased at wholesale from a manufacturer for each set sold at retail, there is a fixed proportions relationship between the television sets sold at retail and those purchased by the retailers as inputs. This is the simplest realistic case.[10] In Figure 1, D represents the retail demand for television sets and S_1 represents the supply of television sets at retail before the manufacturers began to fix prices. When the television sets are sold at noncollusive wholesale prices to the retailers, the corresponding retail price is P_1, and the number of television sets purchased by consumers is Q_1. When the manufacturers collusively raise the wholesale price, the retailers' costs rise and supply shifts from S_1 to S_2. The new retail price-output configuration

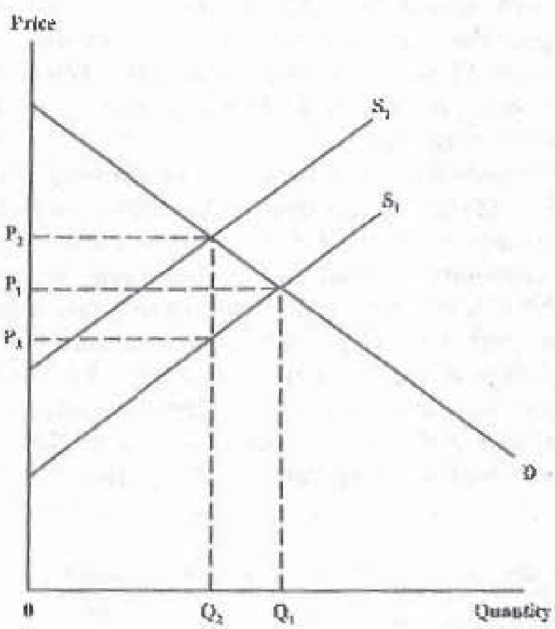

Figure 1

10. The pass-on problem disappears in extreme cases involving combinations of perfectly elastic and perfectly inelastic supply and demand; see R. Harris & L. Sullivan, *supra*, 128 U. Pa. L. Rev at 283–87.

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is P_2 and Q_2, respectively. The vertical displacement in the supply curve represents the collusive overcharge; thus, the overcharge is captured by the difference between P_2 and P_3 in Figure 1. The price to consumers, however, has risen by the difference between P_2 and P_1. In this case, then, the retailers absorb a portion of the overcharge equal to $P_1 - P_3$ while they pass on $P_2 - P_1$ to consumers.

Suppose that all of the determinants of supply and demand are constant except for the cartel formation. In this extreme case, allocating the overcharge damages between direct and indirect purchasers would not be too difficult. Presumably, the retailer could estimate the overcharge on the television sets that it purchased. It would have to compare the collusive price to the price but for the conspiracy. Under the assumed economic conditions, the "but for" price will equal the preconspiracy price. Thus, the retailer can estimate $P_2 - P_3$, and he also knows how much more he is charging for the television sets — that is, he knows $P_2 - P_1$, and as a result, he knows the difference $P_1 - P_3$, which is the amount of the overcharge that he absorbed. The overcharged consumer must estimate the actual overcharge that he experienced — that is, the difference between P_2 and P_1. This too can be easily calculated because the "but for" price equals the competitive price P_1. But we have assumed away the difficulty.

If supply and demand conditions are in flux, which is the usual state of affairs, the direct purchaser will have far more difficulty estimating the "but for" price.[11] He will have to control for changes in nonconspiratorial factors that would have influenced the wholesale price of the television sets absent any conspiracy. This is a complication, but it is not made worse by giving indirect purchasers standing to sue for the overcharges that were passed on to them. The indirect purchasers, however, have to estimate "but for" prices at retail that control for nonconspiratorial factors in the retail market and in the wholesale market. This will be no easy task.

The interests of the retailer plaintiff and the consumer plaintiff are not entirely congruent because what one gets the other does not get. The retailer has an incentive to claim that some portion of the difference between P_2 and P_1 would have occurred anyway — for example, because of other cost changes or demand changes. In this way, the retailer will get to claim more of the overcharge for himself. This incompatibility will cause dissension among the plaintiffs,

11. See ¶394.

which would be bad enough if the retailer and the consumer were joined, but is worse if there are separate suits.

396a2. *Variable proportions.* The measurement difficulties become more interesting and far less tractable when the cartelized product is used in variable proportions in producing the final good. When the manufacturers of such an input conspire on price, their customers will respond by substituting away from the now higher priced input. As a result, the shift in the supply curve will not fully capture the overcharge.[12] To the extent that one can substitute away from the cartelized input, the effects of the overcharge will be blunted. Cooter shows that the total overcharge borne by the consumers can be expressed as[13]

$$Q\Delta P = \left[\frac{\varepsilon}{\varepsilon + \eta}\right](x + 1/2\,\Delta x)\Delta w$$

where Q is the output purchased at the resulting higher retail price, ΔP is the increased price at retail, ε is the elasticity of supply, η is the elasticity of demand, x is the quantity of the cartelized input employed at the higher price, Δx is the change in the quantity employed, and Δw is the change in the price of x due to cartelization. This is obviously a complicated figure to estimate. In fact, the elasticities of demand (η) and supply (ε) are particularly troublesome because one must estimate demand and supply functions first.

But things can get even worse. Consider the additional complication when the product subject to price fixing changes form following its sale. For example, the manufacturers of lysine — an animal feed additive — fixed prices.[14] The lysine was sold at collusive prices to producers of animal feed, who suffered the initial overcharge. The feed was subsequently sold to farmers at prices that reflected the increased lysine cost. The farmers sold cattle to meatpackers at prices that reflected the higher cost of feed due to the higher costs of lysine. It is clear that the meatpackers' prices to retail grocers and restaurants reflected their higher costs. Finally,

12. The extent to which such substitution is possible depends on the production technology. In cases of fixed-proportions production, no substitution is possible.

13. *See* Cooter, *supra*, 129 U. Pa. L. Rev. at 1529, 1532.

14. *See Amino Acid Lysine Antitrust Litig.*, 196 WL 355368 (N.D. Ill. 1996). *See* Ronald W. Cotterill, Leonard Egan, & William Buckhold, *Beyond* Illinois Brick: *The Law and Economics of Cost Pass-Through in the ADM Price Fixing Case*, 18 Rev. Indus. Org. 45 (2001), for an examination of this case.

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396b. An exception for
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16. *Illinois Brick*, 431 U.S. at 736.

17. *See* Comment, *A Legal and Economi*
Hanover Shoe *and* Illinois Brick, 47 U. Chi. :

18. For a brief examination, see Herbe
Cost-Plus Sales, 103 Harv. L. Rev. 1717 (1990)

19. *Kansas v. UtiliCorp United*, 497 U.S.

20. *Id.* at 217.

the ultimate consumer was overcharged at the grocery store or the restaurant due to the lysine cartel. It is obvious that there will be severe problems of proof along this chain from the lysine producer to the ultimate consumer of beef. At each step, one will be faced with estimating "but for" prices. It will become increasingly difficult to prove the extent of any net overcharge as one moves away from the site of the conspiracy.[15] This is the sort of problem that the Supreme Court sought to avoid with its *Hanover Shoe* and *Illinois Brick* decisions.

396b. **An exception for cost-plus contracts.** There is an exception to *Illinois Brick* for preexisting, fixed-quantity, cost-plus contracts. When the direct purchaser has a preexisting contract with its customer(s) that the price it will charge equals the cost of the good being resold plus an agreed upon markup, any overcharge will be passed on in its entirety. If the quantity is specified prior to the resolution of the actual "cost" in the cost-plus contract, then the direct purchaser suffers no loss at all. Under those very limited circumstances, the Court allowed an exception to the *Illinois Brick* rule.[16] If the indirect purchaser has standing under this exception, then the direct purchaser must be denied standing.[17] There are interesting economic problems when the "plus" is an *ad valorem* markup and when the quantity is not fixed,[18] but the Court has decided not to confront these problems and denies standing under those circumstances.

The "cost-plus" exception is rarely used because the requirements are so demanding. The Supreme Court made it quite clear in *Utilicorp* that the window of opportunity for an indirect purchaser has only opened a crack.[19] In *Utilicorp* collusive overcharges on natural gas purchased by utilities were passed on to consumers in the rate structure pursuant to state regulatory procedures. The Court rejected an exception for public utilities that can pass on even 100 percent of the overcharge to their customers.[20] In such a case, the quantity that will be resold is not

15. It should also be fairly clear that the number of potential plaintiffs grows by leaps and bounds as we move away from the site of the lysine conspiracy. This problem would be reduced through class actions, but not all situations are amendable to class treatment.

16. *Illinois Brick*, 431 U.S. at 736.

17. *See* Comment, *A Legal and Economic Analysis of the Cost-Plus Contract Exception in* Hanover Shoe *and* Illinois Brick, 47 U. Chi. L. Rev. 743 (1980).

18. For a brief examination, see Herbert Hovenkamp, *The Indirect Purchaser Rule and Cost-Plus Sales*, 103 Harv. L. Rev. 1717 (1990).

19. *Kansas v. Utilicorp United*, 497 U.S. 199 (1990).

20. *Id.* at 217.